Optimization of energy distribution in smart grids

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Optimization of Energy Distribution in Smart Grids

Ph.D. Thesis

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Distributed Systems Group

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by

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Summary

The power grid is undergoing a substantial change due to the advancements in information technology and the increasing penetration of renewable sources at all scales. This transformation is captured by the term Smart Grid. The evolution towards the Smart Grid paves the road for end-users to become pro-active in the distribution system and, equipped with small-scale renewable energy generators (e.g., photovoltaic panels) and storage systems, to become "prosumers". The prosumer is engaged in both energy production and consumption. Prosumers' energy can be transmitted and exchanged as a commodity between end-users, disrupting the traditional utility model. The appeal of such scenario lies in the engagement of the end-user, in facilitating the introduction and optimization of renewable energy sources, with the overall expectation of optimizing the global energy generation and distribution process in terms of efficiency of operation and asset management. To facilitate the transition to a prosumers' governed grid, we propose a novel strategy for optimizing peer-to-peer energy distribution in the Smart Grid. The strategy is based on prosumer's involvement and considers the energy loss of delivery, the network topology, and the physical constraints of distribution networks. We evaluate the strategy on several synthetic distribution networks based on fundamental topologies: radial, random graph, small-world, and complete graph models. We consider networks of increasing sizes, from 13 to 100 nodes. The results show that the small-world model outperforms the radial model on all efficiency metrics and it is slightly better than the random graph model in overall performance.

We then take one step further and consider a possible scenario in which the prosumer can provision also with energy storage systems to save electrical energy that is produced but not utilized immediately. After fulfilling its individual demands, prosumers can sell and distribute their surplus energy among each other in the same distribution network, or store the energy into their batteries for later self-usage or reselling. We propose a model of battery storage systems to optimize energy costs for prosumers cooperating with the peer-to-peer energy distribution. The proposed model

includes an approach for estimating the costs of energy production and storage. The evaluation of the model shows that by adopting storage systems one can significantly reduce the energy costs of prosumers and reduce the maximum load of the distribution network.

Samenvatting

Het elektriciteitsnet verandert ingrijpend als gevolg van de ontwikkelingen op het gebied van informatietechnologie en het sterk groeiende aandeel van duurzame energiebronnen. Deze transitie wordt veelal aangeduid met de term "Smart Grid", waarin een actievere rol voor eindgebruikers binnen het distributienetwerk mogelijk is en waar eindgebruikers "prosumers" kunnen worden door zowel op kleine schaal duurzame energie op te wekken als energie op te slaan. Behalve het verbruik van energie produceert een prosumer ook energie dat verhandeld kan worden met andere eindgebruikers, waarmee het traditionele gebruikersmodel wordt verstoord. Wat een dergelijk scenario interessant maakt is de betrokkenheid van de eindgebruikers, waarbij het mogelijk is om het genereren en distribueren van duurzame energie op globaal niveau te optimaliseren. Om de transitie naar een distributienetwerk dat primair door de prosumers wordt geleid te faciliteren, stellen we een nieuwe strategie voor om de peer-to-peer energiedistributie binnen het Smart Grid te optimaliseren. Deze strategie gaat uit van de betrokkenheid van prosumers en houdt daarbij rekening met de energie die verloren gaat tijdens het energietransport evenals de structuur en fysieke restricties van het distributienetwerk. We evalueren de strategie op basis van verschillende synthetische distributienetwerken waarvan de grootte varieert van 13 tot 100 nodes en de topologie gebaseerd is op een van de volgende modellen: radial, random graph, small-world en complete graph. De resultaten tonen aan dat small-world netwerken altijd beter presteren dan radial netwerken. Daarnaast zijn de resultaten voor deze small-world netwerken gemiddeld genomen iets beter dan voor random graphs.

Vervolgens onderzoeken we een scenario waarin prosumers beschikken over de mogelijkheid om energie op te slaan. Nadat prosumers aan hun eigen vraag hebben voldaan, kan een eventueel overschot aan energie worden verkocht of opgeslagen om later te gebruiken of te verkopen. Hiervoor introduceren we een model van het opslagsysteem dat, gebaseerd op schattingen van de kosten van het opwekken en opslaan van energie, de energiekosten van de prosumers die een bijdrage leveren aan de peer-to-peer energiedistributie optimaliseert. De evaluatie toont aan dat het

introduceren van energieopslag de kosten van prosumers significant kan verlagen en dat ook de maximale belasting van het distributienetwerk gereduceerd wordt.

Chapter 1

Introduction

Electricity is the enabler of modern societies and human activities worldwide. All the more so nowadays, when devices and vehicles are powered by electricity everywhere. To be more specific, processing information and communication in our world heavily rely on electricity. Since electrical energy is such an affordable and easily accessible commodity in many countries, we have been used to enjoy the convenient and digital life lit by this form of energy and take its availability for granted. However, its real importance is perceived by people when outages or blackout strike. In fact, the increasing consumption of electricity causes an increasing concern about the environmental impact of electrical energy generation and the dissipation connecting to electricity usage.

In our daily life, electricity usually plays a role of a "carrier" that carries energy transformed from other forms of energy, such as fossil fuels (i.e., coal and oil), wind, sunlight, hydro energy and nuclear energy and transported where needed. Acting as the energy carrier, electricity can be transmitted from its generation points (i.e., power plant) to its consumption points through an infrastructure named "power grid". When we turn on the switch of a television, electricity is immediately available and makes the television work. No matter how far the power generation points are, apparently we are enabled to access the electricity as easily as getting pipe water or fresh air whenever we turn on the switch. Actually, such convenient scenario is achieved by the power grid that is a complex system connecting our daily usage of electricity to the power plants.

The current power grid is an achievement of the 19th and 20th centuries. It is designed to meet the challenge of transmitting a huge amount of electrical energy over a long distance even through a whole continent. A simplified structure of the current power grid is illustrated in Figure 1.1. One sees a typical layered hierarchical organization that consists of a power plant, a transmission part and a distribution part. The power plant is responsible for the bulk energy generation that can supply the electricity usage of a large region, and is usually located in a remote area far from the sites consuming the energy. The transmission works at the high voltage level and it is responsible for the bulk electrical energy transportation on the long distance, from the power plant to substations near energy consumption areas. The distribution part works on the low and medium voltage levels delivering electricity from the substation to the final energy consumers, such as residential and commercial buildings, and industrial factories. The main reasons of this highly hierarchical structure are to prevent energy losses for the long distance transmission of high amounts of electricity, and to minimize energy generation costs by the centralized bulk power plant. Such power grid reflects a principle of energy supply, that is, providing electricity for all energy consumers from one common source is the most economical approach. This principle was born in its historical context where non-renewable energy sources based on fossil fuels were abundant and environmental issues were unknown. However, these factors cannot be neglected in the 21st century. The next generation of the power grid should explore evolutionary paradigms that are applicable to the new context where sustainable energy sources and environmental concerns are taken into account.

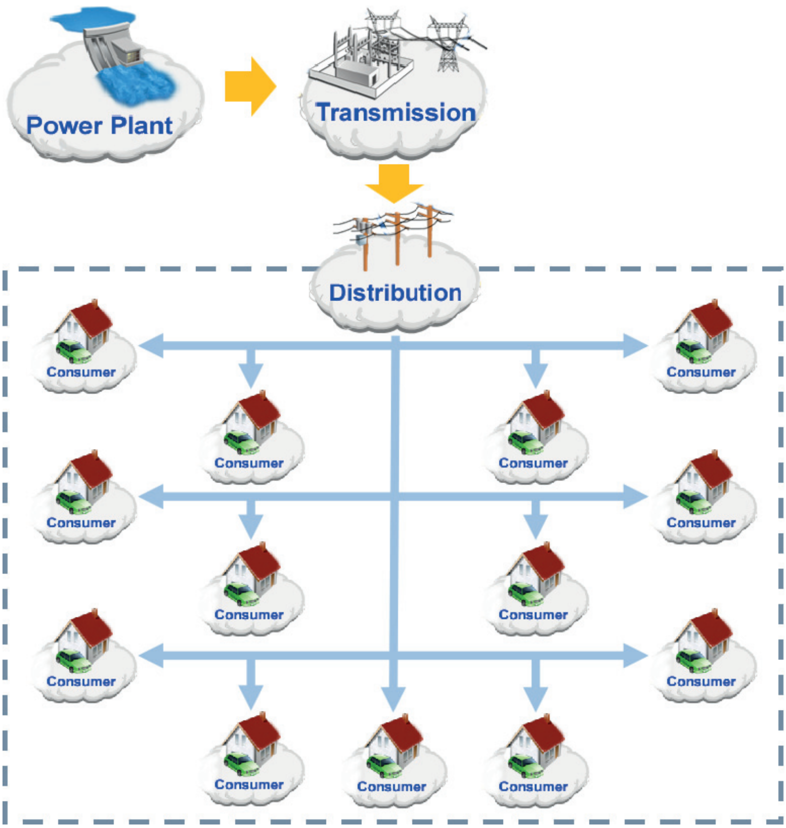

Figure 1.1: The current power grid with highly hierarchical structure.

1.1 Smart Grid: Motivation, Concept, and Vision

The past decade has seen many technological innovations in energy generation from renewable energy sources as well as ICT innovations. This, together with sustainability awareness and economic concerns is strongly pushing for new power grid models. We identify in particular four drivers for change. The first one is the increased penetration of renewable energy source (RES) encouraged by environmental concerns but also the decreased RES generation costs. In order to achieve the goals of bold energy policies, a large amount of renewable energy sources have been integrated within the power grid across the world in recent years. For example, the European Commission has set a goal to increase the share of renewable energy sources to 20% by 2020 [37] and the National Renewable Energy Laboratory (NREL) proposed that the share of wind energy should reach 20% by 2030 [96]. China has a similar target that 30% of the distribution grid should be served by renewable energy sources by 2020 [119]. Japan has an ambitious goal, that is, the share of zero-emission sources in the energy generation should achieve 44% by 2030 [123]. A more ambitious target has been proposed by the Danish Government. By the year 2050, 100% of the energy consumed in Denmark should be generated by renewable energy sources [88]. Until now, Denmark can be considered as one of the most successful countries in terms of integrating renewable energy sources with its existing system. Because the penetration of renewable energy sources in Denmark had reached 44.3% in 2016 [123]. As a consequence, the uncontrollable and uncertain nature of renewable energy sources challenges the operation and reliability of current power grid. In fact, the basic idea behind the design of the traditional power system was that electrical energy generation follows a predictable and controllable output meeting an expected energy demand. The non-renewable energy sources such as fossil fuels are perfectly suitable for this design because of their high controllability. However, the popular and easily accessible renewable energy sources such as solar and wind energy highly depend on natural variability and are very difficult to accurately predict. Therefore, there is the necessity for a new power system that is more flexible in accommodating the variability of energy supply based on the renewable energy sources.

The second motivation lies in that a strong move from the monopoly to an open energy market is undergoing. The commercial organization of the current power grid has a monopoly on energy production, transmission, and distribution, which can be reflected in its highly hierarchical structure. In essence, this process is aiming to dismantle the current monopolistic and oligarchic energy markets. It encourages a large number of parties, including enterprises and end-users, to participate in energy business such as electricity generation, transmission and distribution [29, 59]. The stimulated competition among different parties can provide more choices of energy business to both energy sectors and end-users, which causes more economical and convenient services than the current situation. In the vision above, one notes that it is possible for each end-user to act as a small-scale energy producer and provider. Such an approach is considered beneficial to achieve a future power system having reduced energy losses because of the shorter distance from generation sites to the load sites; and system flexibility [87].

The third motivation for the future grid is the necessity of using modern Information and Communication Technology (ICT) for the operations of the energy sector. The foundation of the current power grid can be traced back to more than a century ago when the ICT technologies were lack-developed. Moreover, in 2003, a meeting involving American utilities companies and U.S. governmental institutions [102] concluded that the status of the current power grid was inefficient and outdated with limited extension capability. It is unable to meet the new efficiency requirements in current information-oriented society and economy [102]. Nowadays, the modern ICT technologies can automatically handle many large scale operations of the power grid, such as meter reading, user connection and disconnection, and network switch operations, which provides opportunities to improve the power grid.

Another motivation point is the increase of distributed energy generation (DEG). The distributed energy generation aims to reduce greenhouse gas emission and to achieve higher penetration of renewable energy sources. It is enabled by the technological and economic availability of small generators producing energy from renewable energy sources, such as photovoltaic (PV) panels (i.e., solar panels) and small wind turbines installed at the distribution level. This aspect poses a challenge to the traditional power system. Because the traditional power system is centralized with respect to energy generation (i.e., thermal and nuclear power generation), energy providers (i.e., electric utility), and operate a hierarchical energy transmission and radial energy distribution networks. In such system, energy is centrally produced and 'pushed' down to the end-users (see Figure 1.1). Therefore, the future power grid, especially at the distribution level, should experience more and more decentralization to accommodate large quantities of distributed energy generation consequent of multi-directional power flows.

The term Smart Grid [92] illustrates the evolution of the power grid. It captures the digitalization of the infrastructure and the related motivations as just presented. More generally, the Smart Grid adopts Information and Communication Technology to improve its efficiency, environmental sustainability, reliability and economics of producing and distributing electrical energy [12, 48]. The traditional model of a power system, with large generation facilities and passive load at the distribution end. However, the Smart Grid introduces distributed energy generation based on renewable energy sources and decentralized energy exchange in distribution networks based on bidirectional flows of energy. Compared to the traditional power system, the promise of the Smart Grid is to provide a much higher efficiency of energy transmission and distribution. If the overall energy loss in the transmission and distribution process of the traditional power systems is approximately 70% [140], the expectation is to bring this as low as 30% [140] for the Smart Grid.

Let us look at an example. Alice wakes up in a sunny morning. It is Sunday. She drives her electric car to go shopping. Alice's house is equipped with photovoltaic panels generating electrical energy in the morning. Because there is limited local energy consumption when Alice is away, the local energy generated by the photovoltaic panels exceeds the local energy demand of the house. Bob is Alice's neighbor and he is busy in this morning. He cooks his breakfast and does house works: cleaning, laundry, exchanging water for his swimming pool. Some household appliances in his house are turned on, including a vacuum cleaner, a washing machine, a dishwasher, an oven, an electric cooker, and a water pump. Although Bob's house is equipped with photovoltaic panels, the locally generated energy is insufficient for the energy consumption in the house. Bob's house looks for an energy provider to buy electrical energy to fulfill its demand. Meanwhile, Alice's house has surplus energy to sell and its energy price is lower than the energy price of the electric utility because locally generated energy is based on renewable energy sources. Then, Bob's house buys energy from Alice's house during the whole morning. In the afternoon, Bob finishes his work and goes out for a party. His house stops buying energy from Alice's house because the local energy generation exceeds the local energy demand. Meanwhile, Alice is back to her home and starts to charge her electric car. The energy consumption in Alice's house is significantly increasing and cannot be satisfied by the local energy generation. This time, Alice's house looks for an energy provider which has surplus energy to sell and it finds Bob's house. For the same reason, Bob offers lower energy price than the electric utility. Then, Alice's house buys energy from Bob's house.

To address scenarios like the one just exemplified, we consider three research questions. The first one is "given an open energy market with real-time pricing possibilities, how to find the cheapest energy provider dynamically and be delivered energy following the paths with minimum energy losses." In the example, Alice and Bob's houses tend to choose providers with cheapest prices to buy energy for saving energy costs. Considering energy losses due, for instance, to resistance, delivery paths to transmit energy from the provider to the houses should be investigated. Because costs of energy losses are involved in the energy costs and energy losses can vary depending on different routes of delivery. The paths that electricity takes in these deliveries strongly depends on the topology of the connectivity between the houses. Because energy can have different routes of delivery depending on the set of pairwise agreements between the houses connected to the distribution network. Then, the second research question is: "how network topology models influence the energy delivery between two points in distribution networks." In the example, we see that Alice's house has surplus energy to sell in the morning but it buys energy in the afternoon. If the house has a home battery to store the surplus energy in the morning, the battery can discharge the stored energy for the demand in the afternoon to save the cost of buying energy from Bob's house. This raises the last question: "how to optimally use the home battery to save energy costs for end-users."

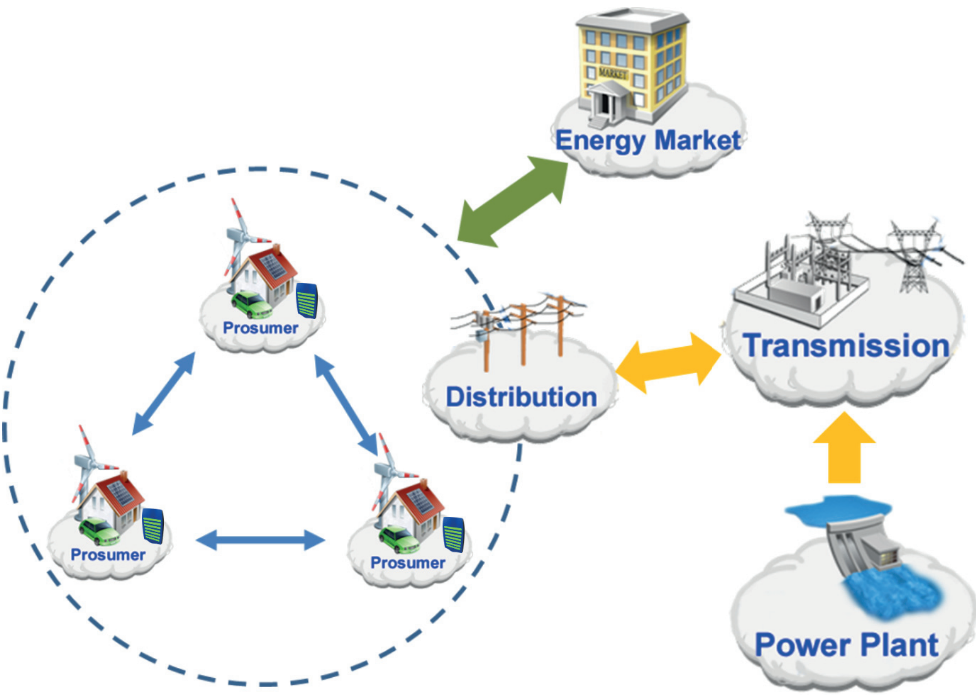

Figure 1.2: The high-level view of the Smart Grid.

In the context of the Smart Grid, we envision a future scenario where renewable energy generators based on photovoltaic panels and small wind turbines enable end-users to produce electrical energy individually and to distribute it freely among each other. In other terms, all end-users are connected to an open energy market at local scale such as the neighborhood or district areas (i.e., in the same distribution network). After fulfilling their individual needs, their surplus energy can be transferred to other end-users that need to buy energy. The motivation for the exchange is monetary. This means that there can be multiple energy providers supplying energy at various prices. The end-user engaged in both energy production and consumption is called a "*prosumer*" (i.e., a producer and a consumer). We use the term "*peer-to-peer energy distribution*" to express the exchange of surplus energy among prosumers in the distribution network. In addition, the prosumer can provision with energy storage systems to save electrical energy that is bought at a low price, or is produced but not utilized directly. After fulfilling the individual demands, prosumers can sell and distribute their surplus energy among each other in the same distribution network, or store the energy into their batteries for later self-usage or reselling. All of the features described above compose a Prosumer-involved Smart Grid. Figure 1.2 shows an high-level view of the interaction among the major Smart Grid stakeholders. This scenario offers two important advantages: decreasing the dependence on consuming energy sources based on fossil fuels; and increasing the independence from centralized schemes for energy generation and operation which is the current adopted model worldwide [12, 48].

1.2 Thesis Scope and Contribution

In the vast domain of the Smart Grid, the present work tackles the following research topics. The first topic deals with strategies for peer-to-peer energy distribution at a local scale to accommodate the energy trading among prosumers. This topic focuses on the low and medium voltage levels of the power grid infrastructure that is close to end-users. The term "local scale" refers to a residential area covered by a sub-network of the distribution network running at low voltage without transformers and substations. We assume a future scenario where prosumers are connected to an open energy market and can exchange electrical energy freely among each other. The motivation for the exchange is monetary. This means that there can be multiple energy providers supplying energy at various prices. We consider distributed renewable energy generation of prosumers, energy loss of delivery, power flows, and topology and physical constraints of the distribution network. The optimization objectives are to reduce energy loss of delivery and to decrease energy costs for the end-users. To achieve these goals, we resort to approaches based on peer-to-peer systems and graph theory. In the Smart Grid, energy can be provided by anyone which has physical cables connected to the consumer and can be delivered to the consumer by routing through a path and passing several prosumers. This scenario is similar to a peer-to-peer network used for file exchanges over the Internet. Prosumers act like peers; physical cables with resistance can be perceived as edges with weights; generated energy with dynamic prices can be viewed as resources shared in the peer-to-peer network but with volume limitations and frequent updates. Moreover, unlike data peer-to-peer systems, there is no buffering and no replication in the Smart Grid.

The second research topic focuses on the distribution infrastructure to support the future scenario where prosumers can freely participate in the energy distribution. We study how the topology of distribution networks affect peer-to-peer energy distribution at the local scale. We evaluate topological effects of four topological models using the Monte Carlo approach [110, 77]. From a topological point of view, we compare the performance of various topological models based on the solution proposed in the first research topic. For the evaluation, we design four assessment metrics: energy loss ratio in the distribution network, energy cost for end-users, maximum load in electric lines, and average path length of energy delivery. The evaluation also covers different scales (i.e., the number of nodes) of distribution networks.

The last topic concerns energy storage systems working at the end-user side. We envision that the prosumer can provision with energy storage systems to save electrical energy that is produced but not utilized directly. After fulfilling the individual demands, prosumers can sell and distribute their surplus energy among each other, or store the energy into their batteries for later self-usage or reselling. We focus on optimizing the operation strategy of the battery storage system by each prosumer cooperating with the peer-to-peer energy distribution and open trading to reduce energy costs for prosumers. We also study how the cost of storing energy influences battery storage systems' performance.

These three topics are closely related: one of the main purposes of the Smart Grid is to promote end-users to save energy, the efficiency of applying renewable energy sources, the flexibility of energy distribution, and the independence of centralized energy generation and control. The Smart Grid with the peer-to-peer energy distribution and trading, running on the new distribution infrastructure and combining with battery storage systems equipped by prosumers, is ongoing towards a more sustainable and reliable power system, and also raises end-users' awareness and interest concerning sustainability and efficiency of energy usage.

Our contribution resides in the several aspects. First of all, we propose an optimization model and a solution of peer-to-peer energy distribution considering prosumers, energy loss of delivery, topology of the distribution network and physical constrains of power flows. The solution can reduce energy loss in the distribution network and energy costs for end-users and dependence from centralized energy generation. The proposed model and solution achieve a balance between purely topological models and detailed power flow models. Thus, we obtain both adequate physical modeling and the scale at which a phenomenon can be observed. Then, we evaluate how the topological models and the model's parameters influence the performance of peer-to-peer energy distribution on the basis of the Monte Carlo approach from the topological point of view. Additionally, we propose a model of battery storage systems cooperating with peer-to-peer energy distribution to optimize renewable energy usage for prosumers and a model of estimating the costs of energy production and storage taking into account the economic factors. Finally, our findings lay the foundations for a Home Energy Management System (HEMS) [61, 81] that supports the end-users in considering evolution scenarios of the distributed renewable energy generation and peer-to-peer energy distribution and trading.

1.3 Outline

The thesis is organized in seven chapters. Chapter 2 provides the relevant background and state of the art. Firstly, we focus on the vision and scenarios characterizing the Smart Grid. Secondly, we review the most related work in the area of peer-to-peer energy distribution and trading on the basis of open energy markets. Third, we analyze and discuss the main studies of peer-to-peer power routing and the power router which are the elements to achieve the peer-to-peer energy distribution and trading. Then, we investigate the main approaches to analyzing and improving the distribution network. Finally, we look at the literature concerning the distributed energy storage and its applications in the scale of distribution networks and end-users.

In Chapter 3, we describe the simulation program that we designed and developed to perform our research related to the Smart Grid. The simulation is performed by the data coming from real markets, energy installations and weather history. We illustrate the architecture of the simulation program and present the methods of simulating prosumers, real-time pricing, energy production, energy consumption, peer-to-peer energy distribution, battery storage systems installed in the prosumer side and distribution networks with various topology models.

Chapter 4 focuses on optimizing peer-peer energy distribution in the Smart Grid considering prosumer involvement, energy loss of delivery, power flows, and topology and physical constraints of the distribution network. The optimization objectives are to reduce energy loss of delivery, to enhance independence from centralized energy generation and central energy providers, and to decrease energy costs for the end-users. To achieve these goals, a mathematical model of the optimization problem, a peer-to-peer model of the Smart Grid and novel algorithms for the power routing are proposed.

Chapter 5 goes further in the peer-to-peer energy distribution with topological considerations. This chapter investigates the role of the topology in facilitating the peer-to-peer energy distribution, that is, how the topology of distribution networks affects the optimal energy distribution at the local scale. We base our investigation on the Monte Carlo approach. The evaluation process is divided into two stages. The first stage is performed on a 37-node network with four topology models: radial, complete graph, random graph and small-world. The second stage tests the random graph model and the small-world model with varying parameters of topology against 100-node networks.

Chapter 6 focuses on the management of the battery storage system by each prosumer. We propose a model of optimizing the operation strategy of battery storage systems for prosumers cooperating with the peer-to-peer energy distribution and open trading. The optimization goal of this model is to reduce energy costs for prosumers. The model provides foundations for a Home Energy Management System (HEMS) on the basis of Smart Homes.

Chapter 7 concludes this thesis and provides some discussion on the presented research topics. It also presents some possible directions and barriers for the future work related to the realization of the Smart Grid.

1.4 Publications

Part of the work presented in this thesis has been published in or, at the time of writing, is under consideration for publication by several journals and conferences. In Table 1.1, we provide an overview of the papers on which this thesis is based and the chapters they are mostly relevant for. We stress that the contributions are to be considered a joint effort with the respective co-authors.

Table 1.1: Publications and manuscripts related to the chapters of this thesis.

<table>
<tr><th>Chapter</th><th>Venue</th><th>Citation</th></tr>
<tr><td>4</td><td>MDPI: Energies</td><td>[116]</td></tr>
<tr><td rowspan="2">5</td><td>The 8th International Conference on Sustainable Energy Information Technology 2018</td><td>[117]</td></tr>
<tr><td>Submitted to journal</td><td>Tech. Rep.</td></tr>
<tr><td>6</td><td>Submitted to journal</td><td>Tech. Rep.</td></tr>
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Chapter 2

State of the Art

The Smart Grid is a vision and also a trend for the power grid. It has received increasing attention and become a popular research topic. Because the current power grid needs to be updated to provide flexibility that can accommodate renewable resources and electric vehicles, and can involve the end-users that no longer passively consume energy, but that can also produce their own energy and feed the surplus energy back to the power grid. Here we provide an overview on the Smart Grid with special focus on the main aspects of this thesis: the vision of the Smart Grid; the study of energy distribution and trading; the study of the topology of the power grid; the status concerning applications involving energy storage systems for the Smart Grid.

2.1 Smart Grid Visions

The traditional way of producing and distributing electrical energy has changed. From a hierarchical system where energy is centrally produced and 'pushed' down to the end-users, we currently have more and more views of involving distributed generation with multi-directional power flows in the lower network layers. In [18], the author briefly describes a vision of the future power grid to solve the growing energy needs and environmental issues. This power grid is composed of small distributed energy generation units where renewable resources play a significant part. The Smart Grid is introduced in [92]. In this article, the authors define the Smart Grid as a secure, agile, and reliable power grid that faces new threats and unanticipated conditions. In [127], the Smart Grid is considered as an Internet-type network where power flows can be transferred like data packets do on the Internet. The authors compare electrical energy with electric data on the Internet, and discuss the key assumptions and requirements that can implement the Smart Grid. According to the authors, one of the key differences between electrical energy and electric data is that electrical energy cannot be stored at a large scale, while electric data can be stored, duplicated, and resent. The solution to transferring electrical energy on the Internet-type network is to create a virtual energy buffer between energy providers and consumers. The virtual energy buffer is implemented through a demand side management strategy which dynamically schedule the electricity usage of every end-user to create a layer of virtual buffer between energy generation and consumption.

Another point of view, the Smart Grid is provided in [57]. In this work, the authors indicate that the main motivations for upgrading to the Smart Grid are the rising greenhouse gas emissions, the emerging requirements for renewable resources and the challenges of security, reliability, and quality of the electrical energy supply. Additionally, the authors emphasize that the transition to the Smart Grid is particularly significant for the electricity distribution network which will be stressed with the new load caused by charging electric vehicles. Thus, the transition of the distribution network will need greater levels of demand-side management, greater flexibility of the system, moving energy generation closer to the loads, and integration of energy storage devices. Then, the authors emphasize that Information and Communication Technology is the key to the Smart Grid; in fact Information and Communication Technology can manage the reliable operation of the power grid in a most economical fashion. In [118], the authors propose a real-time dynamic pricing algorithm as a control method for supply-demand matching to encourage the end-users to change their electrical energy usage. According to [53, 68], a remarkable change of the distribution network is being promoted by enabling end-users to actively participate in small-scale energy production and selling their surplus energy to other end-users. On this basis, an end-user can install photovoltaic panels or a small wind turbine to produce electrical energy locally. The end-user can sell its energy to other end-users when its production excesses its consumption and can buy energy from other end-users when its production does not fulfill its consumption. In this way, the renewable resources can be maximally utilized and energy generation can be moved closer to the loads. While a significant portion of the end-users become both energy producers and consumers, the distribution network will experience a shift from the traditional single energy source to the many, delocalized energy sources. Based on the delocalized energy sources, the work in [147] proposes clustering mechanisms for decentralized energy management by self-organizing end-users into virtual groups where energy supply and demand are locally matched. This work shows the possibility of operating centralized power systems in a decentralized approach based on local information of energy supply and demand. In addition, the simulation results indicate that the increasing the dynamism of the clustering methods can reduce the shortage of energy supply in the clusters.

One of the main motivations for upgrading to the Smart Grid is greenhouse gas emissions. Hledik investigates the environmental benefits of the Smart Grid implementations in [50]. The article firstly presents the impacts of applying the technologies that are commercially available today, such as advanced metering infrastructure

(AMI), varying tariffs, automating technologies, and in-home information display (IHD). Then, it takes an expanded view of the Smart Grid to discuss the possible impacts of future technologies that would be available in the long-term, including the impacts of a smart distribution network and an increase in distributed energy generation. The study points out that the Smart Grid can be seen as an enabler for greener, more efficient technologies and services that would lead to significant energy savings and reduce the greenhouse gas emissions by approximately 16% by 2030. Besides the environmental benefits, the Smart Grid is an overall upgrade of the traditional power grid in reliability of energy supply and distribution networks. Another motivation for implementing the Smart Grid is the challenge of reliability of electrical energy supply. In [95], an analysis based on a reliability perspective of the Smart Grid is provided. The authors critically review the reliability impact of major technologies incorporated into the Smart Grid, which are renewable resources, demand response, and energy storage. The authors also indicate that the growing penetration of electric vehicles will be a significant factor of load growth and become a challenge for the reliability. In addition, the transition towards the Smart Grid is particularly significant for the distribution network [57]. There is discussion about what distribution networks should look like under the scenario of the Smart Grid. Brown analyzes the potential impact of the Smart Grid on designing distribution networks [23]. The author examines new technologies incorporated into future distribution networks including advanced metering infrastructure, distribution automation, and distributed energy generation. From a design perspective, these technologies will result in the meshed network topologies of the future distribution networks and multi-directional power flows, which can adapt to the distributed energy generation and reduce peak demand per customer and improve flexibility of the distribution networks.

In summary, the visions of the Smart Grid involve the following aspects. Integration of renewable resources is essential for the future power grid. The smart grid transition will particularly focus on the distribution network where distributed energy generation, meshed network topologies, multi-directional power flows and energy storage systems will be incorporated. Information and Communication Technology is the key to make this evolution possible via advanced metering infrastructure and automating technologies.

2.2 Peer-to-peer Energy Distribution and Trading

Distributed energy generation units based on renewable resources are growing in number and moving closer to the loads that are pervading the distribution network. As compared to the traditional power grid, small-scale energy generators, such as photovoltaic panels and small wind turbines, connected to the distribution network or to end-user sites are rising in popularity. Since renewable resources are uncertain, how to use renewable resources is one of main barriers to realizing the Smart Grid. An alternative solution for using renewable resources is peer-to-peer energy distribution and trading. A peer in the peer-to-peer energy distribution and trading refers to one or a group of participants which are physically on the same sub-network and are capable of energy production and consumption, including generators, consumers and prosumers. The peers directly buy or sell energy with each other without any intermediation or trading market regulated in a centralized manner. On this basis, the peer-to-peer energy distribution and trading encourages to flexibly use excess energy in an area with different sizes (i.e., residential houses, a neighborhood, a microgrid, and a distribution network) in order to handle unstable energy resources and generated energy. Consequently, the peer-to-peer energy distribution and trading is becoming increasingly studied.

Some works study the strategies for auction or bidding in peer-to-peer energy trading scenarios. For example, in [124], the authors propose an automated double-auction mechanism for the Smart Grid which is modeled as a regional electricity network consisting of prosumers equipped with distributed energy generators based on renewable resources (i.e., photovoltaic panels). The proposed auction mechanism aims to obtain the global optimal price and to achieve an exact balance between demand and supply. Another research proposes an optimal bidding strategy in a microgrid with distributed energy generators based on renewable resources [66]. A microgrid is a small-scale power grid that comprises a cluster of distributed energy generators mainly based on renewable resources and distributes electrical energy in a small geographic area more flexibly and reliably to meet local demands [80]. The microgrid behaves, from the power grid's perspective, as a single energy producer or consumer. The optimal bidding strategy proposed in [66] considers the change of power flows in the connecting line to the main grid, various network and physical constraints. The strategy can improve the expected operating profit of the microgrid by reducing the imbalance cost. Some researches employ approaches based on Game Theory. The work in [80] proposes a multi-leader–multi-follower Stackelberg game for the energy trading among microgrids in a competitive market. The work considers multiple interconnected microgrids in a same region. At a given time, some microgrids have surplus energy to sale or to keep in energy storage facilities, whereas some microgrids need to buy energy to satisfy local demands and/or storage requirements. The games converge to a unique equilibrium solution that maximizes the payoff for all participated microgrids at the equilibrium of the game. This provides an incentive for the energy trading among microgrids in the Smart Grid. Previous works mainly focus on incentive mechanisms for the short-term market, e.g., in [141], a contract game is employed to model the energy trading among small-scale energy providers and consumers to develop an incentive mechanism for the long-term market where energy supply encounters more uncertainty than it is in the short-term market due to the high variability nature of renewable resources. Through the contract game, energy consumers can attract small-scale energy providers to sell energy to them and maximize their own revenue. Small-scale energy providers can also get maximal benefits by selecting the contracts of their own types. The study in [114] considers the energy trading between prosumers, which are end-users that can sell their excess locally generated energy to other end-users with appropriately selected prices and also can buy energy from other end-users, in the same microgrid. A game theoretic approach is adopted to model the interaction between end-users aiming to maximize their own revenue. These end-users compete to sell their excess energy to the local end-users that need energy. The selected price and offered capacity of sold energy depend on both marginal cost of the end-user and prices offered by its counterparts. In [25], Capodieci *et al.* propose a service-oriented agent-based approach to model the energy trading between prosumers. The energy trading strategies used by the agents are inspired from game theory. The simulation results show that the proposed approach can give profit to the prosumers and can balance the power grid. More researches focus on the energy trading on the basis of game theoretic approaches, such as in [86, 142, 128, 90, 132], which model and optimal pricing strategies in the similar context but with different constraints. These study the peer-to-peer energy trading in the Smart Grid from the economic benefit perspective. The main focus is on reaching the equilibrium of energy prices to improve incomes or reduce expenses of participants such as microgrids, energy producers, and consumers.

Another line of research is modeling and optimizing energy exchange in the Smart Grid. Matamoros *et al.* study how energy can be exchanged between two microgrids isolated from the main power grid in order to minimize the total cost of energy generation and transportation, while each microgrid fulfills its local energy demand [93]. The authors propose an approach for both the centralized and distributed cases. The centralized approach is suitable for the case that privacy of information about energy generation is not a concern meaning that two microgrids belong to the same energy operator. On the contrary, the distributed approach is preferable when privacy is of concern. The work in [43] extends the aforementioned approach into the generalized case of multiple microgrids that are fully connected by means of an arbitrary topology. Energy exchange based on intelligent buildings is also investigated by some studies. In [65], Kim and Lavrova optimize power flows in order to exchange energy among intelligent buildings equipped with battery storage systems. The optimization problem is modeled based on the multiple traveling salesmen problem and it is solved via a genetic algorithm. The proposed solution can reduce the transmission line losses and improve energy dissipation balance to reach stability among many intelligent buildings in the Smart Grid. In another work, Mocanu *et al.* propose a Building Energy Management Systems (BEMS). The intelligent buildings equipped with Building Energy Management Systems are enabled to exchange energy among each other, especially with the neighbor intelligent buildings to optimize their energy scheduling and energy costs [94]. The proposed framework combined with an optimization problem is modeled by dynamic game theory and stochastic optimization. The optimization goal is to improve supply-demand balancing subject to keeping a good level of comfort for people in the buildings. In [40], Georgievski *et al.* propose an approach to controlling an office environment and to coupling it with dynamic pricing from the Smart Grid. The proposed approach schedules the operation of devices in the office environment according to policies defined by the users, in order to save energy and overall energy bill costs. The approach considers both the case of a building equipped with energy generators based on renewable resources and the case without such installation. With the development of communication technologies, mobile networks rapidly increase their contributions to the global energy consumption. The optimization of smart grid-enabled mobile networks is investigated in [55]. In this article, Huang *et al.* present a model of energy exchange among base stations (BSs) of mobile networks for minimizing energy bought from the electric utility for the base stations. In this model, each base station is equipped with a renewable energy generator and acts like a prosumer. It consumes the energy produced directly and transfers surplus energy to other base stations that need energy without charging any cost. The proposed solution can save about 18% energy bought from the main power grid. In this research line, the researches mainly focus on the strategies of exchanging and sharing energy and balancing supply-demand among peers where the economic benefits of peers are not the key objective.

Energy exchange and trading among prosumers is one of the most significant innovations that the concept of the Smart Grid can bring to energy distribution. The PowerMatcher City project demonstrates energy exchange and trading on a local energy market among a small set of prosumers connected to the same distribution network [14, 69, 74, 35, 136, 51, 72, 34, 135, 68, 20, 70, 91, 71, 73, 67]. End-users, owning home appliances, electric vehicles and/or industrial installations, act as small electrical energy consumption. Small-sized distributed energy generators based on renewable resources provide small energy production in the operation of the electricity infrastructure. In this way, the PowerMatcher City integrates large amounts of renewable energy in the power grid while avoiding overloads in the distribution network. The aim of the project concerns the problem of supply and demand matching. A market-based control approach is employed to optimally use the possibilities of energy production and consumption to alter their operation and to increase their overall match performance. The PowerMatcher City project is validated both in the field deployment and in simulation studies with good results. It can improve the match between energy consumption and the availability of renewable energy production, and can reduce the imbalance caused by unpredictable behavior of renewable resources. In addition, it is able to relieve overloaded distribution networks.

2.3 Peer-to-peer Power Routing and Power Router

To implement the peer-to-peer energy distribution, peer-to-peer power routing is studied. In the Smart Grid, the peer-to-peer power routing refers to a mechanism that allows to transfer electrical energy from a source (sender) to a destination (receiver) which can be, but is not necessarily a geographical neighbor. The power router is a device that connects power devices and/or peers trading energy into a network structure and manages electrical power flows and information data flows among them [139, 47]. Similar to an Internet router forwarding data to the destination through various paths, the power router can realize the direction and quantity control of power flows and dispatch energy to its destination. The power router is the key solution to the peer-to-peer power routing and serves as a critical component in the Smart Grid.

The scenario that electrical energy can be delivered like data packets in the Smart Grid is presented in [126]. In this work, the concept of Open Electric Energy Network (OEEN) is proposed to tackle the challenge of effectively integrating distributed energy generation and small-scale energy providers. In the Open Electric Energy Network, power flows and supply-demand balance are controlled by multiple Electric-Energy-Routers (EERs). The electrical energy of a transaction is treated as an Electricity-Power-Packet (EPP) that is an energy package wrapped with an information tag containing the locations of energy provider and consumer. The Electricity-Power-Packet is transmitted from the energy provider (source) to the consumer (destination) in a peer-to-peer way. Inspired by this idea, Hikihara *et al.* propose a system working at physical layer to dispatch electrical energy by power packets from a source to a destination [121, 125]. The power packet means that electrical energy is treated like data packets tagged with the information about senders and receivers. The concept of power packet dispatching is defined as that N energy sources supply electrical energy to M loads based on the demand. The system proposed by [121, 125] implements a power packing mechanism. The packed power can be transmitted between sources and loads according to the demands. A power packet is a voltage wave consisting of a header, a payload, and a footer. The header includes a start signal and an address signal. The payload carries electrical energy, and the footer has an end signal. The power packet is sent by time-division multiplex (TDM) which can distinguish the energy for each sources. The power router is responsible for handling and forwarding power packets. After receiving power packets, the power router sorts them by their tagged information and sends them to other routers or objective loads. Reza and Lu propose a new structure of the power packet [111]. This improved power packet removes several non-compulsory bits to improve the switching efficiency. Furthermore, the operational principles and an implementation of a power router from the perspective of power electronics is presented in [115]. The work in [41] processes an experimental validation of a power router. The experiment proves that the concept of the power router is feasible and the results show that the power flows can be fully controlled by the power router. These papers provide the physical foundation scheme to realize peer-to-peer power routing.

Additionally, the implementation of peer-to-peer power routing is predicated on the robust and scalable communication that can provide control information about the status of the power grid and coordination functionality among power routers [21]. In [108], the authors describe how the power router is influenced by telecommunication restrictions. In contrast, the work in [21] proposes a new communication architecture that facilitates the realization of the power routing concept on the basis of power routers. The proposed communication architecture consists of three layers: physical control layer, power flow routing layer, and power flow control layer. Each layer provides specific services (i.e., information and control operations) to the layers above and below according to power routing requirements. More importantly, these layers provide the main communication functionalities required by power routers, which are coordination, power grid status update, and control. These works provide the communication foundation scheme to realize peer-to-peer power routing. Notice that the robust and scalable communication should be empowered by an equally well designed software architecture. In this respect, Zhong *et al.* propose a software architecture for the power router network in [144]. The work aims at building a hierarchical energy control architecture that can implement the peer-to-peer power routing.

A power router is also the subject of [98, 97, 99, 100] in which Nguyen *et al.* present the cost-scaling, push-relabel algorithm to control the power flow in distribution networks considering the distributed energy generation, bidirectional power flows, and meshed network topology. Based on such power router, Zhu *et al.* design a power routing protocol to find the most energy efficient path for power flows from one house to another house [145]. This protocol focuses on the data security perspective on the power routing to tackle the challenge that is how to detect and defend major attacks against power routing protocols. The secure power routing protocol developed by the authors can detect most internal attacks, such as spoofed route signaling and fabricated routing messages, by using message redundancy. It provides securely and optimally power routing for exchanging renewable energy in the Smart Grid. In [22], Brocco proposes a distributed protocol to create and maintain energy delivery paths between energy sources and loads devices. The work focuses on the power router design with the autonomous control protocol and analysis on potential side-effects of power routing that are route leaking and power flow inversion. Also, Lin *et al.* propose an architecture that encapsulates the desired features of the power router in [84]. The architecture is amenable for both implementation and theoretical study of the peer-to-peer power routing. Focusing on the power routing strategy, Hong and Kim propose a strategy utilizing game theory for optimizing power routing among prosumers or microgrids in [52]. The main aim of their strategy is to choose desired transaction prices according to energy surpluses and shortages for prosumers or microgrids in order to maximize their profits through energy transactions. The strategy is designed for the power router. It is divided into two sub-strategies: an optimal transaction price decision approach for selling and purchasing the surplus energy of prosumers or microgrids; and a power routing approach satisfying the amount of energy supply or demand. The strategy mainly focuses on the economic perspective. Hence, the optimization of transaction prices and power routing are modeled as a traditional transportation problem to balance the energy supply and demand. It does not consider the topology and physical constraints of the distribution network. In [133], Wang *et al.* present the design of a power router that is responsible for power dispatching. The design includes the hardware structure of the router and a power routing algorithm based on graph theory and lowest cost selection. The proposed power routing algorithm is based on the directed graph and considers energy losses of the power routing. The proposed power router also includes an communication protocol on the basis of Open Shortest Path First (OSPF) that is a protocol widely used to exchange information on the Internet. The design considers how to cooperate the power routing and information exchange processes in the power router. Ma *et al.* propose a power dispatching protocol based on the power router that links all distributed energy generators and energy consumers and centrally controls all participants [89]. The protocol focuses on matching energy consumers with suppliers, balancing the load and generation, and scheduling energy delivery in the distribution network. To match energy consumers with suppliers, a standard matching problem is employed to maximize each participant's benefit by developing a deferred acceptance algorithm. The scheduling problem is solved by a heuristic solution that can obtain the real-time balance between the load and generation, taking into account the urgency of energy transit and fairness among the participants.

Table 2.1 compares the proposals on the basis of five characteristics that are central to power routers ([98, 97, 99, 100, 145, 22, 84, 52, 133, 89]). The characteristics are energy loss, transit capacity, power flow conflict, trading management and network topology. They are defined as follows: (i) Energy loss stands for the energy loss during the power transit. (ii) Transit capacity is the power capacity of electric lines and/or other devices relating to the power transit. (iii) Power flow inversion represents the conflict between two power flows with reversed directions that are transferred in one electric line. Because one electric line is impossible to transfer two power flows with different directions at the same time. (iv) Energy trading management includes deciding energy prices and matching supply-demand pairs for energy sellers and buyers. (v) Network topology means whether the proposed strategy considers any specific topology of the distribution network. There are ten works summarized in Table 2.1. As shown in this table, power flow inversion is rarely studied. Only one work ([22]) discusses the power flow inversion as a power routing pitfall. Energy loss and transit capacity are relevant popular characteristics. Both of them are addressed in six works. Moreover, there are four works ([98, 99, 84, 89]) consider both energy loss and transit capacity in their peer-to-peer power routing strategies. Meaning that these two characteristics are significant for the peer-to-peer power routing. For the network topology, there are five works ([98, 97, 99, 100, 133]) utilize the directed graph in the proposed strategies. Other works do not consider this characteristic. It should be noted that these works only consider simple topologies which are normally unsuitable for the implementation of distribution networks. Finally, in [52, 89], the proposed strategies are designed to have multiple features such as bidding energy prices and matching supply-demand pairs for energy sellers and buyers. Since these features are based on the global optimization, they are necessarily centralized thus not fit for peer-to-peer distribution.

Table 2.1: Characteristics of the power routing strategies.

Work	**Energy Loss**	**Transit Capacity**	**Power Flow Inversion**	**Energy Trading Management**	**Network Topology**
[98]	√	√			Directed Graph
[97]		√			Directed Graph
[99]	√	√			Directed Graph
[100]		√			Directed Graph
[145]	√				
[22]			√		
[84]	√	√			
[52]				√	
[133]	√				Directed Graph
[89]	√	√		√	

2.4 The Topology of Energy Distribution

To study the network topology influence on the efficiency and resilience of power grids, complex networks analysis (CNA) has been gaining popularity because it allows to highlight key global features of a system on the basis of topological measures [105]. Usually, the complex networks analysis is employed to get information about robustness and resilience to failures of transmission grids (i.e., high voltage networks). For example, Crucitti *et al.* study the structural vulnerability of the Italian transmission grid based on complex network approaches. They show correlations between the topology of a power grid and the tolerance of the system against cascading failures [30]. A similar approach is found in [15, 146], where Albert *et al.* study the American power grids showing that disturbances of the transmission substations with the highest load can greatly affect the ability of transferring electrical energy in the power grid. Moreover, Chassin and Posse identify the scale-free model as the typical network topology and study the reliability of the North American Eastern and Western electric transmission grids based on such model [26]. In [113], Rosas-Casals considers the European electric transmission grid as a complex network and analyzes the fragility and major malfunctions of the grid. Han and Zhang study the reason for cascading failures of transmission grids based on the small-world model [49]. The works introduced above mainly focus on transmission grids while distribution networks (i.e., medium and low voltage networks), have been mostly neglected.

However, the Smart Grid mostly affects the medium and low voltage networks [57]. The topological study of distribution networks is one of the focal points of the upgrade. Brown highlights that the topologies of distribution networks have an important influence on electrical energy distribution and need to upgrade from non-radial topologies to meshed ones with respect to distributed energy generation from the energy distribution's perspective [23]. This standpoint is further emphasized in [36] where the adoption of a meshed distribution network is shown to have the potential to reduce energy losses and to facilitate distributed energy generation. To support the increasing connection of the distributed energy generation, Alvarez-Herault *et al.* propose approaches to upgrade the distribution network topology from the current radial shape to a meshed network [16].

There are a few researches on topologies of distribution networks to support peer-to-peer energy distribution and trading dominated by prosumers. In [104], Pagani and Aiello consider possible evolution of the distribution networks towards the Smart Grid. In particular, the authors provide a topological analysis of the Dutch distribution networks and assess the topological properties' influence on the cost of peer-to-peer energy distribution and trading in the Smart Grid. This work offers an analysis of the medium and low voltage distribution networks of the North Netherlands using statistical tools of the complex network analysis. This analysis goes beyond the study of existing distribution networks. It also proposes an approach to evaluating the distribution infrastructure in terms of its capability to support the peer-to-peer energy distribution and trading. In addition, it concludes that global topological statistical measures of distribution networks can influence prosumers' eagerness to trade energy. Based on this evolution trend of distribution infrastructure, Pagani and Aiello analyze the lower layers of the distribution network from a static topological point of view [106]. This study assesses several graph models (e.g., small-world graphs and random graphs) using approaches from the complex network analysis perspective. It also provides a quantitative evaluation of how the topology improvement influences the costs of electrical energy transportation. The goal of this work is to discover which topological models are most appropriate for supporting the peer-to-peer energy distribution and trading, and how network topology models influence the cost of electrical energy delivery in the distribution network. The contribution of this work highlights the importance of topological models for enabling the peer-to-peer energy distribution and trading in the Smart Grid. The assessment results indicate that the small-world model of the topology with average degree $\langle k \rangle \approx 4$ can provide a balance between the performance and the cost of deployment and operation of local energy exchange. This study can provide a budgeting and decision support tool for governmental organizations and utility companies. Additionally, in [107], Pagani and Aiello take a practical step in defining a methodology for evolving any existing distribution network to support the peer-to-peer energy distribution and trading, taking into account the physical constraints. To do so, the authors consider several possible evolution strategies and evaluate them by the Dutch distribution networks. The topologies of samples from the medium and low voltage distribution networks in the Netherlands are analyzed. The analysis considers the benefits in terms of connectivity, the construction costs for the electric lines expansion for the evolved distribution networks, and the benefits in terms of electricity distribution costs and resilience. This work provides the foundations to build decision support systems for governmental organizations and utility companies.

2.5 Residential Energy Storage System

The rise in the penetration of renewable resources is accompanied by the rise in energy storage systems installed at the residential level. The energy storage system can act as a buffer of electrical energy and decouple the time of energy generation and demand by storing electricity in off-peak hours and withdrawing it in the peak demand hours.

Some works study the individual energy storage system, that is, the storage device is equipped and used by the individual end-user. In [129], the authors address the problem of deciding whether to fulfill energy consumption by purchasing electricity from the power grid or discharging from the energy storage under variable demands and prices, as well as up to what level to charge or discharge the energy storage. The problem solved in this paper is modeled as a Markov decision process and the result shows a two-threshold stationary cost-minimizing policy for deciding charging or discharging the energy storage. In [122], the authors propose an econometric model aiming at quantifying the average peak-shaving value and the average lifetime of the battery storage system operated by the end-user under dynamic prices. This work formulates the problem of maximizing the average value of the battery storage system as a stochastic shortest path and derives a closed-form expression for the average battery lifetime. Zheng *et al.* propose an agent-based model to explore the opportunities of arbitrage for residential energy storage systems under time-varying electricity tariffs [143]. However, these works do not consider the influence of renewable energy generation operated by the end-user. Considering the integration of renewable resources for load supply, the works [54, 134, 82] and [58] design the cost-effective management of energy storage on the end-user side. They apply similar approaches to formulate the control optimization problem aimed at minimizing the energy costs.

Another line of research focusing on the topic of sharing energy storage systems among end-users has recently attracted growing interests. Bayram *et al.* propose a sharing-based architecture of the energy storage system for a group of end-users [19]. The proposed architecture is employed as peak-hour energy management systems and a detailed economical analysis of this proposal indicates that the sharing-based architecture is economically beneficial at the residential level. In [83], the authors focus on the management strategy and load scheduling of shared energy storage at the end-user site equipped with a renewable generator. This paper presents a real-time solution for the management strategy and load scheduling to minimize the overall system cost. The work in [131] studies the influence of coordination and peak-shaving operation of the individual energy storage systems in a mixed residential and commercial neighborhood with a high share of renewable resources. The simulation results show that the coordination of the individual energy storage systems is beneficial for the end-users and the peak-shaving operation of the energy storage is beneficial for the distribution network operator. Similarly, the work in [85] introduces the cloud energy storage (CES), which is also a shared energy storage solution that provides energy storage services to end-users. This work considers the investment and operating decisions of both the CES operator and the end-users to reduce the cost of energy storage. Additionally, the work in [62] studies the specific problem of sharing energy storage systems to arbitrage against time-of-use tariffs from the electric companies' point of view. The investment decisions made by the electric companies are modeled as a non-convex and non-cooperative game. From the distribution network's point of view, the paper [33] proposes a control approach which shares a part of the storage capacity of the energy storage systems installed at the end-user side in the distribution network. The proposed approach can benefit both the end-users and distribution network operator. Among the aforementioned works, [83, 85] and [33] consider renewable energy generators installed at the residential level with modeling operation strategies of energy storage systems. On the other side, the authors of [19] and [62] also focus on shared energy storage at the residential level but without considering the renewable energy generators installed at the same level.

In summary, the works related to the residential energy storage system mainly focus on reducing energy costs for end-users and on strategies of sharing energy storage installed at the distribution level. The cooperation between residential energy storage systems and renewable energy generators installed by end-users has not gained much attention.

Chapter 3

Simulation Program

The vision of the Smart Grid described in Chapter 1 is far from being realized. Although there are small scale testbeds (e.g., PowerMatcher [67]) where some features of the Smart Grid are implemented, simulation is mainly used to study the Smart Grid. Given the cost and time to physically study the future grid, we also perform the research related to the Smart Grid based on a simulation program that we design and develop. The simulation involves prosumers, real-time pricing, energy production, energy consumption, peer-to-peer energy distribution, distribution networks with various topology models, and energy storage systems equipped by the prosumers.

3.1 Structure of Simulation Program

We perform the simulation based on the data coming from real markets, energy installations and weather history. Such choice enables us to implement a realistic simulation of real-time pricing, energy consumption and energy production from small-scale renewable generators. The simulation program is written in the Java programming language. A representation through a block diagram of the modules involved and implemented in the simulation program is shown in Figure 3.1.

The simulation program is composed of two parts which are "Simulation Management" and "Smart Grid Simulation Engine." The role of Simulation Management is to run evaluation cases on the Smart Grid Simulation Engine and to record the raw data of the simulation results into files. These two functions are handled by the modules named "Evaluation Case" and "Result Data Collection," respectively. The Smart Grid Simulation Engine consists of three modules which are "Energy Data," "Distribution Network," and "Energy Distribution." These modules are responsible for generating energy data of prosumers (i.e., energy production, consumption and price), establishing distribution networks with different topology models, and performing energy exchange and trading among prosumers. The Smart Grid Simulation Engine plays the key role in the simulation program. We provide its details in the following section.

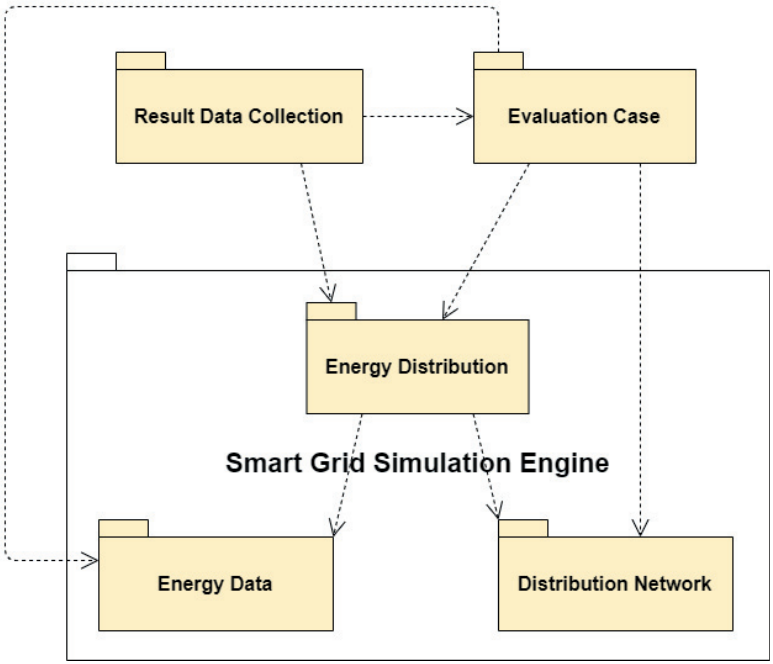


Figure 3.1: Modules of the simulation program.

3.2 Smart Grid Simulation Engine

Figure 3.2 shows the main class diagram of Smart Grid Simulation Engine. The module of Energy Distribution simulates energy exchange and trading among end-users or prosumers in traditional and peer-to-peer ways. In Figure 3.2, the class of "End-user" represents the pure consumer that is not equipped with any renewable generator. The class of "Prosumer" is the End-user which has an object of the class "Renewable Generator." The class "Photovoltaic Panel" and "Wind Turbine" represent two types of the renewable generators. The energy storage installed at the residential level is presented by the class of "Energy Storage System" which is a composition of the class of Prosumer. To handle the different ways of energy distribution, we have an interface "Power Flow Pattern" which is implemented by "Centralized Energy Distribution" and "Peer-to-peer Energy Distribution." The class of Centralized Energy Distribution represents the traditional way of energy distribution where electrical energy is centrally produced and pushed down to all end-users by the electric utility. The class of Peer-to-peer Energy Distribution implements energy exchange and trading among prosumers. This module is responsible for searching the suitable energy providers for consumers and managing how to deliver energy to consumers according to the topology information and physical constraints of the distribution network. The class of "Power Flow" represents a path transferring energy from an energy seller to a buyer. An object of this class indicates the nodes composing a path and energy amount that the path carries.

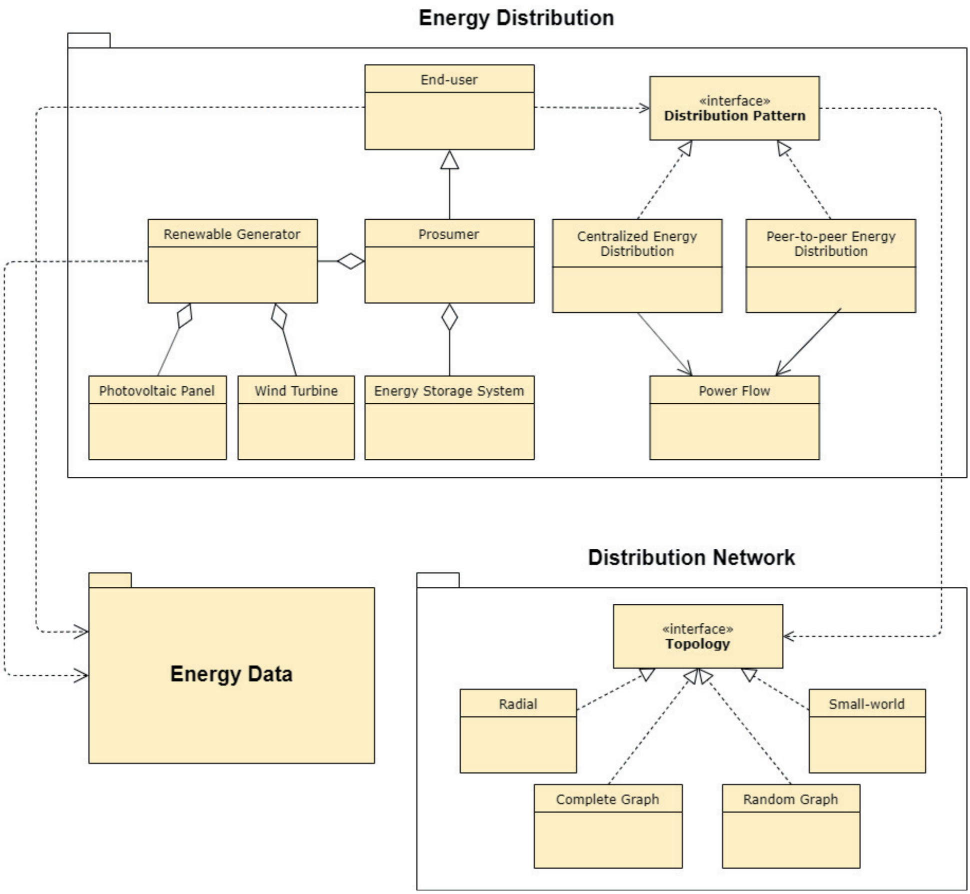


Figure 3.2: Main class diagram of the Smart Grid Simulation Engine.

The module of Distribution Network simulates distribution networks with various topology models. To handle different topology models, we have an interface "Topology." The classes "Radial", "Complete Graph", "Random Graph", and "Small-world implement the interface and are responsible for generating networks based on the radial model, complete graph model, random graph model, and small-world model.

Energy Data is one of the central modules in the Smart Grid Simulation Engine, which generates the data about energy of prosumers including energy price, energy consumption and energy production from small-scale renewable generators. It consists of six sub-modules, shown in Figure 3.3, which are responsible for specific simulation tasks.

- Wind Energy Production. Its role is to simulate a small wind turbine that can produce electricity from wind. The simulation of wind energy production is based on the specific types of small wind turbines and is dependent on wind speed.
- Solar Energy Production. Its role is to simulate the photovoltaic panel that can produce electricity from solar radiation. The simulation of solar energy production relies on the relevant weather data which are cloud coverage of sky, and sunrise and sunset times.
- Energy Consumption. It simulates how much energy is consumed by an end-user or prosumer.
- Energy Price. It simulates the real-time pricing for selling surplus energy of prosumers.
- Weather History. It provides historical weather data that can support the simulation of solar and wind energy production. The weather data include temperature, air pressure, wind speed, solar radiation, cloud coverage of sky, and sunrise and sunset times.
- Random Generator. Its role is to generate random numbers with various probability distributions.

In this module, the simulation follows two different approaches. The first one simply generates wind speed, solar radiation, energy consumption and energy price based on the historical data coming from the Internet. The second approach resorts to Monte Carlo Simulation which is a stochastic simulation and is largely used to study power systems (e.g., [27, 109]). The Monte Carlo Simulation can take into account more possible scenarios than with the deterministic approach. The approach relies on generating repeated random numbers [110, 79]. In our case, this entails the use of statistical distributions for modeling energy consumption, renewable energy production, and real-time pricing. The following chapters specifically illustrate these two approaches and their application to the simulation.

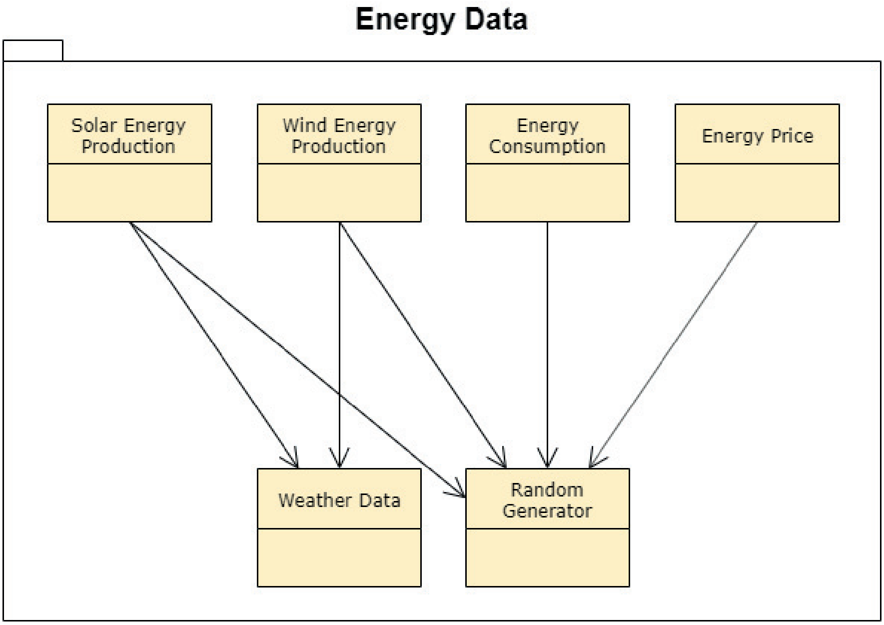


Figure 3.3: Energy Data Simulation Module.

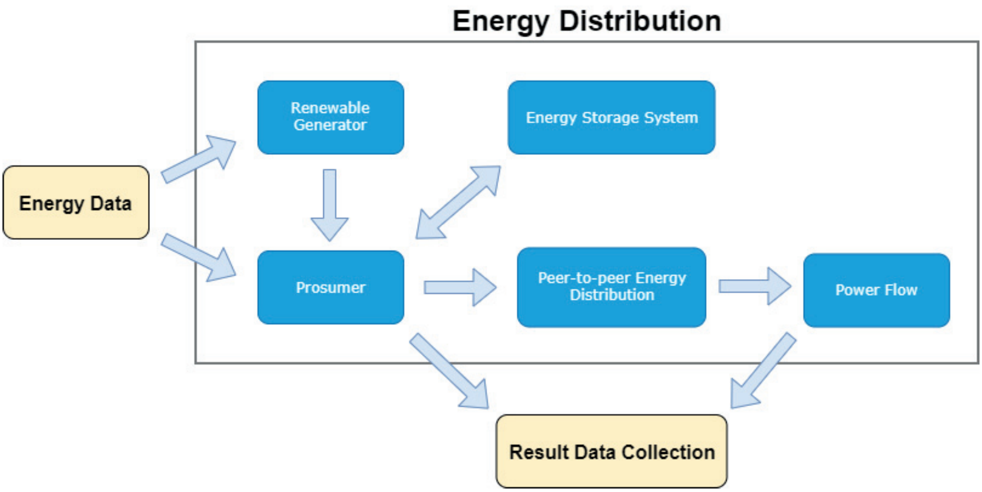


Figure 3.4: Data flows between components of the simulation program.

3.3 Data Flows in Simulation Program

Figure 3.4 illustrates data flows between components of the simulation program to show how the the components cooperate in the simulation process. The data flows start from Energy Data which generates data of wind energy, solar energy, energy consumption, and energy prices. The data go to Renewable Generator and Prosumer. Prosumer also receives energy generation data from Renewable Generator and exchanges information about battery with Energy Storage System. In the following phase, Prosumer transfers data of searching energy providers to Peer-to-peer Energy Distribution. Peer-to-peer Energy Distribution sends data of all providers and energy delivery paths from providers to the consumer to Power Flow. Finally, all data converge on Result Data Collection and written into files to be recorded.

Chapter 4

Route of Peer-to-peer Energy Distribution

The term *peer-to-peer energy distribution* expresses the trading of surplus energy among prosumers in the distribution network. In the context of the network, peer-to-peer is about dynamic routing. By contrast, centralized energy distribution is that end-users buy energy from or send their surplus energy to a centralized operator. This chapter focuses on optimizing the route for peer-to-peer energy distribution in the Smart Grid considering prosumer involvement, energy loss of delivery, topologies, power flows, and physical constraints of the distribution network. Next we provide details of the model we propose.

4.1 Assumptions

We make the following assumptions for our model. End-users without any (renewable) energy generators are simply consumers. The other end-users equipped with (renewable) energy generators are prosumers. The prosumers produce energy for their own consumption or for resell. Any node can be a buyer and the price for energy is set dynamically per transaction. The electric utility, seen as a seller with infinite capacity, also sells energy and has to cater system's balance against a profit. In a given time slot, a prosumer acts as a provider selling energy to consumers, if its energy production exceeds its energy consumption. In the opposite case, a prosumer becomes a consumer buying energy from providers or the electric utility. The distribution network delivers energy from the providers to the consumers with possible energy losses and under the governing physical constraints. All end-users are connected to an energy market to trade energy negotiating at real-time prices. Energy prices in the energy market fluctuate depending on tariffs offered by the providers. The market's borders are defined by the topology of the infrastructure and are therefore geographical in nature. More precisely, the model uses the following assumptions.

- Buying and selling energy are random discrete events.
- Buying or selling energy is an autonomous decision of each prosumer.
- Buying, selling and transmitting energy, in different time slots are independent events.

- At any given time slot, a prosumer can only be a consumer or a provider, not both.
- The providers prefer selling energy to the peers rather than the electric utility.
- The consumers prefer buying energy from the peers rather than the electric utility.
- Energy delivery entails a non-null energy loss.
- Energy losses are only due to power line transit.
- The cost of energy losses is paid by the consumer.
- The compensation of delivery energy losses is not considered.
- Only active power in the distribution network is considered.
- Voltage instability in electric lines is not considered.

4.2 Mathematical Model

We define a weighted electricity distribution graph as one where nodes and edges represent end-users (including prosumers) and the electric lines connecting the end-users, respectively. The substations and transformers are not considered in the graph. The electric lines are differentiated according to their electrical resistance, and thus are modeled as weighted edges. According to the electrical resistance of the electric line, we can calculate the energy loss in this line. The edges are considered directed to represent the flow. The direction of the edge is dependent on the time slot, that is, it can change at different times. Each electric line has an ampacity which represents its capacity for the flow. Formally, we have

4.1. Definition (Weighted Electricity Distribution Graph). *An electricity distribution graph is a weighted graph $G(V, E, W, H, Q)$ such that each element $v_i \in V$ is an end-user that is a consuming unit of a physical distribution network. If there is an edge $e_{ij} = (v_i, v_j) \in E$ between two nodes, there is a physical electric line connecting directly the elements represented by v_i and v_j. The weight of the edge e_{ij} is $w(e_{ij}) \in W$ that is the electrical resistance of the physical electric line connecting v_i and v_j. The capacity of the edge e_{ij} is $h(e_{ij}) \in H$ that is the ampacity of the physical electric line connecting v_i and v_j. Each $v_i \in V$ is associated with a value $q_i \in Q$ which indicates its supply or demand depending on whether $q_i > 0$ or $q_i < 0$.*

In the weighted electricity distribution graph, we have

4.1. Theorem. *Between any two nodes, a path $PATH(i, j) = \{e_{ia}, e_{ab}, ..., e_{xj}\}$ represents a set of physical electric lines connecting v_i and v_j.*

As a point of notation, given a system with p end-users, let $EU = \{eu_1, eu_2, ..., eu_p\}$ denote these end-users. Let $T = \{\Delta t_1, \Delta t_2, ...\}$ where $\Delta t_i = \Delta t_j$ $(i \neq j)$ denote a set of time slots. A set of energy consumers and providers at Δt is denoted by $EC(t) = \{ec_{t,1}, ec_{t,2}, ..., ec_{t,n}\}$ and $EP(t) = \{ep_{t,1}, ep_{t,2}, ..., ep_{t,m}\}$, respectively. For each provider, we have $ep_{t,i} = (price_{t,i}, supply_{t,i})$, where $price_{t,i}$ represents the energy price (€/kW·h) of $ep_{t,i}$ and $supply_{t,i}$ represents an amount of energy supplied by $ep_{t,i}$. The amount of energy that $ec_{t,i}$ buys from $ep_{t,j}$ is represented by $buy_{t,(i,j)} \in (0, supply_{t,j}]$. The energy generated and consumed by $eu_{t,i}$ are represented by $GE_{t,i}$ and $CE_{t,i}$, respectively. Thus, we have $Q_{t,i} = GE_{t,i} - CE_{t,i}$ representing the amount of energy which $eu_{t,i}$ is able to sell or needs to buy. If $Q_{t,i} > 0$, $eu_{t,i}$ has surplus energy to sell. If $Q_{t,i} < 0$, $eu_{t,i}$ needs to buy energy to fulfill its demand. If $Q_{t,i} = 0$, $eu_{t,i}$ is self-satisfied.

4.2.1 Objective Function

In the proposed model, the power flow will follow varying paths which depend on the set of pairwise agreements between nodes per time slot and the physical constraint of keeping the system in demand-offer balance. This also means that energy losses on the network will vary per time slot. Since energy losses are paid by the buyer, the buyer has the interest to make energy provisioning decisions that are optimal with respect to losses. In other words, the individual optimization goal can be presented as: "how to search the cheapest energy providers considering energy price and energy transit losses, and how to find delivery paths with minimum energy loss."

For a consumer $ec_{t,i}$, the cost of buying an amount of energy x is defined as $CoB(x)$. The energy loss of delivering x to the consumer is defined as $LoD(x)$. The delivery path from $ep_{t,j}$ to $ec_{t,i}$ is $PATH(j,i) = \{e_1, e_2, ...\}$ where $PATH(j,i)$ consists of electric lines $\{e_1, e_2, ...\}$ without substations and transformers. Energy loss in an electric line $e \in PATH(j,i)$ is defined as LS_e. Thus, energy loss of a delivery path $PATH(j,i)$ is the sum of LS_e in all electric lines $\{e_1, e_2, ...\} \in PATH(j,i)$. Then, in case of $Q_{t,i} < 0$, the objective function of optimizing energy cost of $ec_{t,i}$ at any given time slot is the following:

$$\begin{cases} CoB(|Q_{t,i}|) = \min \displaystyle\sum_{j=1}^{|EP(t)|} (price_{t,j} \cdot (buy_{t,(i,j)} + LoD(buy_{t,(i,j)}))) \\ LoD(buy_{t,(i,j)}) = \min \displaystyle\sum_{\forall PATH(j,i)} \left(\sum_{e \in PATH(j,i)} LS_e \right) \end{cases} \tag{4.1}$$

4.2.2 Production and Consumption Constraints

Since a prosumer can only act as a consumer or a provider at any given time slot, we have Equation (4.2). Meaning that a prosumer cannot buy and sell energy at the same time slot.

$$EC(t) \cap EP(t) = \emptyset \tag{4.2}$$

The set of consumers and providers is a subset of the set of nodes. Then, we have that Equation (4.3). It is possible that some prosumers are self-satisfied at a given time slot.

$$EC(t) \cup EP(t) \subseteq EU \tag{4.3}$$

At each time slot, the total energy consumption and the total energy supply in the distribution network have to be the same. Since prosumers are not necessarily able to provide the energy to all consumers, a super agent (i.e., an electric utility) is part of the model with the ability to buy or sell energy at fixed prices when end-users' demand and supply are unbalanced. The super agent sells energy at a price and buys energy at a lower price than it sells.

The amount of energy balanced by the super agent at Δt is represented by $ES(t)$. Positive values of $ES(t)$ ($ES(t) > 0$) represent the selling of energy by the utility, negative values ($ES(t) < 0$) represent buying. Three constraints represent the condition that the system has to be always in balance.

$$|Q_{t,i}| = \sum_{j=1}^{|EP(t)|} buy_{t,(i,j)} \tag{4.4}$$

$$\sum_{i=1}^{|EC(t)|} |Q_{t,i}| = \sum_{j=1}^{|EP(t)|} supply_{t,j} + ES(t) \tag{4.5}$$

$$\sum_{i=1}^{|EC(t)|} CE_{t,i} = \sum_{j=1}^{|EP(t)|} GE_{t,j} + ES(t) \tag{4.6}$$

4.2.3 Constraints on Ampacity and Power Flow Direction

Two physical system's constraints are part of the model: ampacity and flow directionality. Ampacity of an electric line e_k is the maximum electric current $I_{e_k}^{max}$ carried by the electric line [45]. The ampacity is related to the voltage U_{e_k} in the following way $I_{e_k}^{max} \times U_{e_k} \times \Delta t$. The power flow starting from $ep_{t,j}$ going through e_k is represented by $f_{(e_k, ep_{t,j})}$. This leads to:

$$\sum_{ep_{t,j} \in EP(t)} f_{(e_k, ep_{t,j})} \leq I_{e_k}^{max} \cdot U_{e_k} \cdot \Delta t \tag{4.7}$$

On a given line at a given time slot, there can be only one direction of flow, that is, the direction of $f_{(e_k,ep_{t,j})}$, represented by $d_{(e_k,ep_{t,j})}$ takes values in the pair: $\{-1,1\}$. For example, if there is a power flow in an electric line from point A to B at Δt, another power flow in this electric line from point B to A at the same Δt is not allowed.

$$\sum_{ep_{t,j}\in EP(t)} d_{(e_k,ep_{t,j})} = |d_{(e_k,ep_{t,j})}| \tag{4.8}$$

4.2.4 Optimization Problem

The proposed model can be cast as a minimum-cost flow problem (MCFP) [13]. The providers and consumers in the distribution network can be considered as the sources and sinks in the minimum-cost flow problem, respectively. The electrical resistance and ampacity of the electric line are associated with the cost and capacity of transferring flows in the network, respectively. The optimization problem is to find the possible paths of transferring a certain amount of power flows from the providers to the consumers with the lowest costs. The optimization problem can be stated as follows:

$$\begin{aligned}
\min \quad & CoB(|Q_{t,i}|) \\
s.t. \quad & \begin{cases}
|Q_{t,i}| = \sum_{j=1}^{|EP(t)|} buy_{t,(i,j)} \\
\sum_{i=1}^{|EC(t)|} |Q_{t,i}| = \sum_{j=1}^{|EP(t)|} supply_{t,j} + ES(t) \quad (EC(t)\cap EP(t)=\emptyset) \\
\sum_{i=1}^{|EC(t)|} CE_{t,i} = \sum_{j=1}^{|EP(t)|} GE_{t,j} + ES(t) \qquad (EC(t)\cap EP(t)=\emptyset) \\
\sum_{ep_{t,j}\in EP(t)} f_{(e_k,ep_{t,j})} \le I_{e_k}^{max}\cdot U_{e_k}\cdot \Delta t \\
\sum_{ep_{t,j}\in EP(t)} d_{(e_k,ep_{t,j})} = |d_{(e_k,ep_{t,j})}|
\end{cases}
\end{aligned}$$

4.2.5 Energy Loss Calculation

Energy loss is computed by state information of each electric line. In the distribution network, electric power is delivered as alternating current (AC). In the AC system, the value of electric current and voltage can be expressed in the form of root mean square (RMS). The RMS value is the effective value of alternating current or voltage. It is equivalent to the value of the direct current (DC) that provides the same effect in a resistive load [31]. Therefore, we applied RMS values of alternating current and voltage to the energy loss calculation. The symbols for the calculation are defined in Table 4.1 as follows.

Table 4.1: The symbols used in energy loss description.

Symbol	**Stand for**	**Unit**
P	electric power	kW (kilo watt)
W	electrical energy	kW·h (kilo watt hour)
I	electric current	A (ampere)
U	voltage	kV (kilo volt)
Δt	time slot	hour
R	electrical resistance	ohm
L	energy loss	Wh (watt hour)

Based on the definition of Electric Power, electrical energy transmitted in a conductor is:

$$W = P \cdot \Delta t = I \cdot U \cdot \Delta t \tag{4.9}$$

We can then compute the electric current I (Equation (4.10)) and the calculation of energy loss L in the conductor (Equation (4.11)):

$$I = \frac{W}{U \cdot \Delta t} \tag{4.10}$$

$$L = I^2 \cdot R \cdot \Delta t = \left(\frac{W}{U \cdot \Delta t} \right)^2 \cdot R \cdot \Delta t = \frac{W^2 \cdot R}{\Delta t \cdot U^2} \tag{4.11}$$

Defining L_i the energy loss of an electric line in a delivery path, then the total energy loss in the delivery path $PATH(a, b)$ is denoted by $LOSS_{ab}$.

$$\begin{cases} L_1 = \dfrac{W^2 \cdot R_1}{\Delta t \cdot U_1^2} \\ L_i = \dfrac{\left(W - \displaystyle\sum_{k=1}^{i-1} L_k \right)^2 \cdot R_i}{\Delta t \cdot U_i^2} \\ LOSS_{ab} = \displaystyle\sum_{i \in PATH(a,b)} L_i \end{cases} \tag{4.12}$$

4.3 Algorithms

4.3.1 Peer-to-Peer Model of the Smart Grid

In our proposed model, end-users are represented as nodes/peers; electric lines with electrical resistance are arcs with weights; produced energy has varying/dynamic prices for given finite amounts, while buffering and replication do not exist. Arc directions can change at different time slots, as they represent flows, and are finite in capacity.

4.3.2 Arc Dynamic Direction Matrix

To address the constraints of ampacity and power flow directionality (Section 4.2.3), we design a data structure called Arc Dynamic Direction Matrix (M_{ADD}). In M_{ADD}, each element denotes an arc and represents the state of the arc including its energy capacity, the amount of energy that it carries and its power flow direction. The value of energy capacity of the arc (i, j) is fixed and it is represented by $M_{ADD}(i, j).AMP$. The information relating to the power flow is described by the value of $M_{ADD}(i, j)$, and defined next.

$$M_{ADD}(i,j) \begin{cases} > 0, M_{ADD}(j,i) = -M_{ADD}(i,j) & \text{a power flow from } i \text{ to } j; \\ = 0, M_{ADD}(j,i) = 0 & \text{no power flow;} \\ = -M_{ADD}(j,i), M_{ADD}(j,i) > 0 & \text{a power flow from } j \text{ to } i; \\ = NIL, M_{ADD}(j,i) = NIL & \text{no connection between } i \text{ and } j. \end{cases} \tag{4.13}$$

If $M_{ADD}(i, j) > 0$, there is a power flow in the arc (i, j) (from i to j). The value of $M_{ADD}(i, j)$ is the amount of energy carried by the power flow. The value of $M_{ADD}(j, i)$ is $-M_{ADD}(i, j)$. On the contrary, if $M_{ADD}(i, j) = NA$, there has to be a power flow in the arc (j, i). Hence $M_{ADD}(j, i) > 0$. If $M_{ADD}(i, j) = 0$, there are no power flows in (i, j) and the value of $M_{ADD}(j, i)$ has to be 0 too. Moreover, $M_{ADD}(i, j) = NIL$ means that there are no arcs between i and j (i and j are disconnected). The initial value of each element in M_{ADD} is 0 or NIL according to the topology of the distribution network.

M_{ADD} is used to check whether an arc is available to transmit electrical energy. Electrical energy is able to transmitted from the node i to the node j, only if i and j are connected; and there are no power flows from j to i in the arc (i, j); and the value of $M_{ADD}(i, j)$ is less than $M_{ADD}(i, j).AMP$. This is the key step when optimizing delivery paths for peer-to-peer energy distribution in the distribution network. To check the presence of an arc, we design Algorithm 1.

Algorithm 1 Find nodes that are available to transmit electrical energy for the node i. The node j is available for the node i, only if i and j are connected; and there are no power flows from j to i; and the arc (i, j) has sufficient energy capacity.

```
procedure FIND-AVAILABLE-NODES(i)
    Global variable: M_ADD
    Input: source node i
    Output: a set of nodes
    for each node j in M_ADD and j ≠ i do
        if M_ADD(i,j) ≠ NIL and M_ADD(i,j) ≠ NA and M_ADD(i,j) < M_ADD(i,j).AMP then
            nodes ← j
        end if
    end for
    return nodes
end procedure
```

4.3.3 Delivery Path Optimization

We extend Dijkstra's algorithm [28] to find a shortest path from the provider node i to the consumer node j. In this algorithm, when visiting a node, the key step is to find its connected nodes that are available to transmit electrical energy using the Arc Dynamic Direction Matrix (M_{ADD}). To measure the weight of an arc, we use R/V^2. Because V and R are the parameters that reflect the characteristics of the electric line, Equation (4.11). The resulting algorithm for finding the shortest-path in a weighted graph is Algorithm 2.

Algorithm 3 identifies multiple delivery paths with power flows. After finding the shortest path from the provider node i to the consumer node j, Algorithm 3 checks whether this path has sufficient energy capacity to transmit the electrical energy injected by the provider. The energy capacity of a path is determined by the arc with the minimum energy capacity. If the capacity is sufficient, the algorithm ends with the identified delivery path. Otherwise, the algorithm calculates the amount of energy that cannot be transmitted among the path and finds alternative available delivery paths from i to j to transmit the rest of energy. This process continues until all the energy injected by the provider can be transmitted or there are no more paths from i to j, Algorithm 3.

Algorithm 2 Find the shortest path from a source node to a destination node based on a weighted graph and the Arc Dynamic Direction Matrix.

```
procedure FIND-SHORTEST-PATH(source, dest)
    Input: source node
    Input: destination node
    Output: a set of nodes as the shortest path
    distance[] ← ∞                                         ▷ Initiate all elements.
    previous[] ← NIL                                       ▷ Initiate all elements.
    distance[source] ← 0
    for all nodes in the graph do
        u ← extract unvisited node of minimum distance[u]
        if u is dest then
            stop this for loop
        end if
        nodes ← FIND-AVAILABLE-NODES(u)                    ▷ Refer to Algorithm 1.
        for each adj in nodes do
            alternative ← distance[u]+ get weight by R/V^2 of arc (u, adj)
            if alternative < distance[adj] then    ▷ A shorter path to v has been found.
                distance[adj] ← alternative
                previous[adj] ← u
            end if
        end for
    end for
    path ← get the nodes of the shortest path in previous[]
    return path
end procedure
```

Algorithm 3 Plan power flows from a provider to a consumer. The algorithm plans one or multiple paths to transmit energy from the provider to the consumer considering the energy capacity of each electric line.

procedure PLAN-ENERGY-FLOWS($source, dest, E$)
  Input: source node
  Input: destination node
  Input: amount of energy to transmit
  Output: one power flow or a set of power flows
  Output: amount of energy that cannot be transmitted from the source to the destination
  while $path \leftarrow$ FIND-SHORTEST-PATH($source, dest$) is successful **do** ▷ Refer to Algorithm 2
    $capacity \leftarrow$ calculate energy capacity of ($path$)
    if $capacity \geq E$ **then**
      $flows \leftarrow path$ with E ▷ a $flow$ is a $path$ with the energy it transmits.
      $rest \leftarrow 0$
      update M_{ADD}'s elements relating to $flows$
      stop this **while** loop
    else
      $flows \leftarrow path$ with $capacity$ ▷ $capacity$ is the amount of energy that $flow$ transmits.
      $rest \leftarrow$ calculate the rest amount of energy that cannot be transmitted
      update M_{ADD}'s elements relating to $flows$
    end if
  end while
  return $flows$ and $rest$
end procedure

4.3.4 Optimization Step

Since one consumer's need is not necessarily satisfied by a single provider, then the computation of energy loss needs special attention. If multiple providers transmit different amounts of energy to one consumer, comparing the values of energy loss is not applicable. We define the proportion of loss ($loss\%$) as the percentage of energy loss in all delivery paths. For each provider, we calculate the cost based on transmitting the same amount of energy to the consumer. This is the estimated cost that is only used for comparing providers. Algorithm 4 identifies the optimal providers for a specific consumer.

If the demand of consumers exceed the productions of prosumers, then the utility has to intervene. The consumer has to buy the rest of energy from the electric utility at a fixed price. We assume that the electric utility injects energy to the distribution network at a fixed node. Then, calculating energy loss of buying energy from the electric utility is the same as calculating the energy loss of delivering energy from the fixed node to the consumer. Algorithm 5 considers this case.

4.3.5 Example of Optimization

To illustrate the working of the proposed algorithms, we provide a small and representative example of their execution. Consider the network shown in Figure 4.1. It consists of five nodes and six arcs. To simplify the example, we assume that the electrical resistance of each arc is 3 Ohm and the voltage of each arc is 1 kV. Arc $< A, B >$, $< B, C >$, $< C, D >$ and $< A, D >$ have the same energy capacity that is 10 kW·h. Arc $< A, E >$ and $< D, E >$ have the same energy capacity that is 20 kW·h. The time slot for this example is 1 h, i.e., $\Delta t = 1$ h. We start with Node A being a consumer. Its energy demand is 20 kW·h. Node C and Node D are providers. Each of them provides 20 kW·h with the price of EUR 0.15 per kW·h.

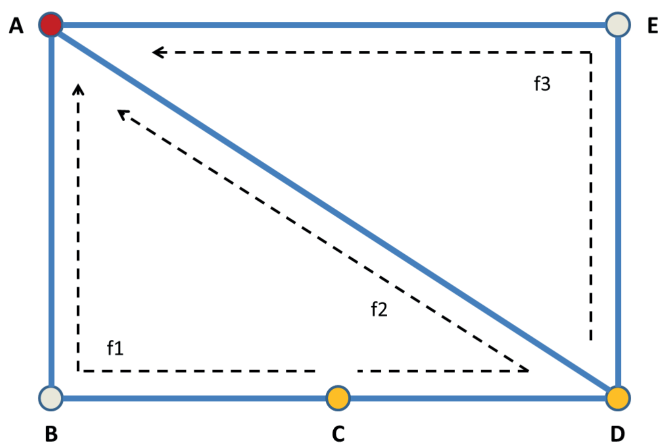


Figure 4.1: A simple example to describe the procedure of the algorithms proposed in this section.

Algorithm 4 Find optimal providers for a consumer

procedure FIND-OPTIMAL-PROVIDERS($consumer, E$)
    Global variable: M_{ADD}
    Global variable: all providers in Δt that is $EP(t)$
    Input: consumer node
    Input: amount of energy to buy
    Output: one provider or a set of providers selected to buy energy
    Output: amount of energy that cannot be supplied by the providers
    for each provider ep_i in $EP(t)$ **do**
        $buy_i \leftarrow$ amount of energy that can buy from ep_i
        $flows_i, rest_i \leftarrow$ PLAN-ENERGY-FLOWS($consumer, ep_i, buy_i$)▷ Refer to Algorithm 3
        $loss_i \leftarrow$ calculate energy loss in $flows_i$
        $loss_i\% \leftarrow loss_i/(buy_i - rest_i) \times 100\%$
        $estimate_i \leftarrow E \times (1 + loss_i\%) \times ep_i.price$ ▷ Estimate cost of buying E with $loss_i$ from ep_i.
    end for
    while $EP(t)$ has unvisited ep_i **do**
        $providers \leftarrow ep_i$ with minimum $estimate_i$ in $EP(t)$
        if E is fulfilled **then**
            $rest \leftarrow 0$
            stop this **while** loop
        else
            $rest \leftarrow$ calculate the rest amount of energy to buy
        end if
    end while
    update states of selected ep_i in $EP(t)$
    return $providers$ and $rest$
end procedure

Algorithm 5 Calculate energy cost for consumer

procedure CALCULATE-ENERGY-COST($consumer, E$)
  Input: consumer node
  Input: amount of energy to buy
  Output: energy cost
  $providers, rest \leftarrow$ FIND-OPTIMAL-PROVIDERS($consumer, E$) ▷ Refer to Algorithm 4
  $cost_p \leftarrow \sum cost_i$ of all ep_i in $providers$
  if $rest > 0$ **then**
    $loss_u \leftarrow$ calculate energy loss of transmitting $rest$ energy from electric utility to consumer
    $cost_u \leftarrow price_u \times (rest + loss_u)$ ▷ $price_u$ is the price offered by the electric utility.
  else
    $cost_u \leftarrow 0$
  end if
  $cost \leftarrow cost_u + cost_p$
  return $cost$
end procedure

The procedure starts from Algorithm 5 that is launched by Node A. At the beginning of Algorithm 5, Algorithm 4 is called to find providers and get their energy costs for the consumer. Algorithm 4 calls Algorithm 3 to organize power flows for Node C and Node D that are providers. Algorithm 3 calls Algorithm 2 to find the shortest paths for Provider C and Provider D and Algorithm 1 is called by Algorithm 2 to get adjacent nodes. In this example, we assume that Provider C is processed before Provider D. Firstly, Algorithm 2 returns a shortest path $f1 : C \rightarrow B \rightarrow A$ for Provider C. Then Algorithm 3 checks whether the energy capacity of this path is sufficient to transmit the energy required by Node A. Since the capacity of $f1$ is 10 kW·h that is insufficient, Algorithm 3 calls Algorithm 2 again to get another path $f2 : C \rightarrow D \rightarrow A$ for Provider C. After checking the capacity by Algorithm 3, $f1$ and $f2$ are able to fulfill the demand of Node A. When processing Node D, the arc $< A, D >$ is not available. Because $f2 : C \rightarrow D \rightarrow A$ has taken all the capacity of $< A, D >$. Therefore, Algorithm 2 returns the path $f3 : D \rightarrow E \rightarrow A$ for Node

D. After checking the capacity by Algorithm 3, this path has the sufficient capacity for transmitting 20 kW·h to Node A. When Algorithm 3 returns, energy loss is calculated by Equation (4.12) in Algorithm 4 and energy costs are calculated in the same algorithm. For $f1 : C \to B \to A$, the energy loss in $C \to B$ and $B \to A$ are 0.3 kW·h and 0.28 kW·h respectively. The total energy loss of $f1$ is $0.3 + 0.28 = 0.58$ kW·h. For $f2 : C \to D \to A$, its energy loss is same as $f1$. Thus, Provider C has $loss\% = (0.58 \times 2)/20 = 5.8\%$ and the energy cost $(20+0.58\times 2)\times 0.15 = 3.17$ EUR. For $f3 : D \to E \to A$, the energy loss in $D \to E$ and $E \to A$ are 1.2 kW·h and 1.1 kW·h respectively. For Provider D, the total energy loss is 2.3 kW·h with $loss\% = 11.5\%$ and the energy cost is $(20 + 2.3) \times 0.15 = 3.35$ EUR. Then, Provider C is selected to buy energy and the delivery paths are $f1 : C \to B \to A$ and $f2 : C \to D \to A$. Finally, Algorithm 5 returns the energy cost of Node A as 3.17 EUR and the procedure ends.

4.3.6 Performance Analysis

We use N to denote the number of nodes and use M to denote the number of arcs. The number of providers at a time slot is denoted by S. The distribution network of the Smart Grid is a connected graph. This means that there are no disconnected end-users in the distribution network.

In Algorithm 1, the for loop checks all nodes in the graph. Its running time is $O(N)$. The running time of Algorithm 2 depends on how we implement the $distance[]$ that contains the values of weight in Line 5. Because this decides the performance of searching the minimum value in Line 9 of Algorithm 2. Numbering the nodes from 0 to $N - 1$ and we store the values of weight in the elements of an array indexed by the node number. Therefore, the performance of Line 9 in Algorithm 2 is $O(N)$. In the main for loop starting from Line 8 of Algorithm 2, the running time of Lines 9 and 13 are both $O(N)$. The running time of the for loop starting from Line 14 of Algorithm 2 is $O(M)$. Then, the performance in the main for loop is $O(N + N + M) = O(N + M)$. Since the main for loop runs $N - 1$ times, the overall performance of Algorithm 2 is $O((N - 1) \times (N + M)) = O(N^2)$.

In Algorithm 3, Line 8 compares all the arcs in a path to find the arc with the minimum energy capacity. Its running time is $O(M)$. Updating elements in Lines 12 and 17 both run N times. The performance of Line 7 is $O(N^2)$ as discussed above. How many times the while loop runs is difficult to measure. Because it is decided by the number of paths from the source node to the destination node and the energy capacity of these paths. Considering the number of paths between two nodes is no more than the number of arcs in a graph, we estimated that the while loop runs no more than M times. Thus, the complexity of Algorithm 3 is

$O(M \times (N^2 + M + N)) = O(N^2 + M^2)$.

In Algorithm 4, the for loop in Line 8 and the while loop in Line 15 both run S times. The performance of Line 10 is $O(N^2 + M^2)$ as discussed above. Based on Equation (4.12), the worst case complexity of calculating energy loss in a delivery path is $O(M^2)$. In Line 16, the time consumed by selecting the provider with minimum estimated cost is $O(S)$. Outside of the loops, the running time of updating $EP(t)$ is $O(S)$. Thus, the overall performance of Algorithm 4 is $O(N^2+M^2+S^2)$. Since $S \leq N$, the performance is given by $O(N^2 + M^2)$.

The complexity of Algorithm 5 is decided by Algorithm 4 (in Line 5). Therefore, the overall performance of the whole solution is $O(N^2+M^2)$. In practice, the distribution network is normally not a complete graph because of the high construction costs of the infrastructure. Therefore, there are only a few paths between two nodes. In Algorithm 3, the times of running while loop should be $T_{while} \ll M$. In this case, the performance of the proposed solution is $O(N^2)$. It is beyond the scope of the present treatment to identify whether the given complexity is a lower bound to the problem at hand.

4.4 Simulation

To verify the solution developed in Section 4.3, we build a simulation program to represent the Smart Grid. This simulation program involves end-users, prosumers, real-time pricing, energy production, energy consumption, energy loss of delivery and a distribution network based on an IEEE test feeder. To make the simulation realistic, relevant data are generated according to open datasets available on-line [2, 5, 3, 1].

The simulation program is written in Java. It ran on a standard desktop computer with Intel Core i3-4160T CPU at 3.10 GHz, 8.0 GB installed memory (RAM), Windows 7 Enterprise 64 bit Operating System and Java Version 8 Update 73.

4.4.1 Simulation of Distribution Network

For the simulation we use a standard IEEE Distribution Test Feeder consisting of 13 nodes and three phases. The original test feeder is presented in [64]. Its complete data can be downloaded at `http://ewh.ieee.org/soc/pes/dsacom/testfeeders`. We make some modifications to adapt this test feeder for our simulation. Considering the switch, transformer, and regulator are not involved in our model, we close the switch; substitute the in-line transformer for a line; substitute the regulator for a node. We use the desired voltage on a 120 volt base as the voltage for all lines in the test feeder. We focus on the active power and assume that all of the nodes in this test feeder are end-users. Another assumption is that distributed loads of different phases are balanced. Meaning that all phases in this test feeder have the same behaviour in terms of the distributed load. The topology of this modified test feeder is shown in Figure 4.2.

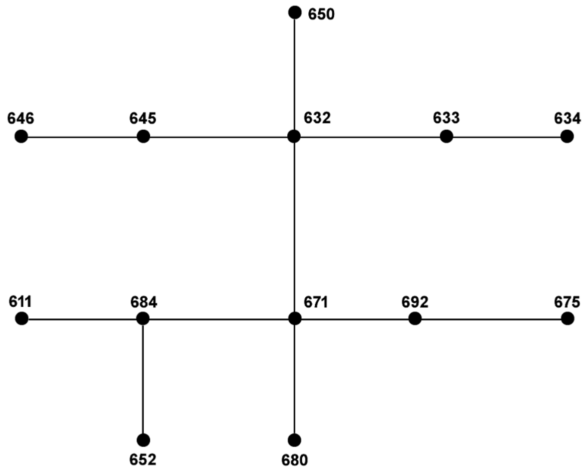


Figure 4.2: The modified IEEE 13-bus test feeder.

4.4.2 Simulation of Wind Energy Production

Small wind turbines and the photovoltaic panels are the typical small-scale energy generators adopted by prosumers. We associate to each prosumer either a wind or solar generator. We randomly chose one of the generators for energy production at the beginning of the simulation. Wind power flowing through a wind turbine is dependent on the length of the turbine's rotor blades, air density, and wind speed. The height of the wind turbine also influences the wind power, due to the different wind speed [46]. In our simulation, we chose a small wind turbine mounted on a residential building. The total height of the installed wind turbine is limited. Therefore, we neglect the influence of the height. The formulas of generating electric power P_w by a wind turbine, and calculating electrical energy E_w are derived from [46], shown next:

$$\begin{cases} P = 0.5 \times A \times \rho \times V^3 \times C_w \\ P_w = \min(P, P_{max}) \\ E_w = P_w \times \Delta t \end{cases} \tag{4.14}$$

The units of P_w and E_w are Watt and Joule, respectively. The area swept by the rotor blades (m^2), air density (kg/m^2), and wind speed (m/s) are represented by A, ρ

and V, respectively. We use $C_w \in (0, 1)$ to represent the efficiency of a wind turbine, and P_{max} (Watt) is the maximum power output. For air density, we use the average value $\rho = 1.225$ [56].

In the simulation, we use the data of a small wind turbine Evance R9000 (Wind-Power (accessed on 8 April 2016): `www.wind-power-program.com/small_turbines.htm`) where $A = \pi \times (5.5/2)^2$, $C_w = 0.35$ and $P_{max} = 5200$.

We base the wind speed on actual data from our local airport: Eelde [2]. Eelde is the airport of Groningen in the Netherlands. These data are provided by Koninklijk Nederlands Meteorologisch Instituut (`http://www.knmi.nl/home`) (Royal Netherlands Meteorological Institute). These data provide the minimum hourly mean wind speed $\bar{v}_{min}$ and the maximum hourly mean wind speed $\bar{v}_{max}$ from 1st January 1906. We only use the data of year 2015 for the simulation.

In the process of the simulation, we produce a random boolean value to indicate whether there is wind blowing at that time slot. If the wind exists, we randomly select one day D_r in a year and convert the current time slot to the hour in a day. Then, we are able to obtain $\bar{v}_{min}$ and $\bar{v}_{max}$ of this hour in D_r. Finally, we randomly generate a value between $\bar{v}_{min}$ and $\bar{v}_{max}$ as the wind speed and calculate the wind energy production.

4.4.3 Simulation of Solar Energy Production

The formulas of producing solar power P_s and electrical energy E_s by a photovoltaic panel are shown in Equation (4.15)[1].

$$\begin{cases} P = A \cdot r \cdot C_p \cdot Q \\ P_s = \min(P, P_{peak}) \\ E_s = P_s \cdot \Delta t \end{cases} \tag{4.15}$$

The unit of P_s is Watt and the unit of E_s is Joule. The surface area of a photovoltaic panel (m^2) and solar radiation (W/m^2) are denoted by A and r, respectively. We use $C_p \in (0, 1)$ to denote the efficiency of a photovoltaic panel. We use $Q \in [0.5, 0.9]$ to denote the Quality Factor (Performance Ratio) that includes all loss relating to the solar power production of the photovoltaic panel. The peak power output of the photovoltaic panel is P_{peak} (Watt).

We assume that all photovoltaic panels are movable and their tilt is adjusted twice a year, in the summer and winter. For residence buildings, fixed or adjustable panels are realistic choices, while tracking panels (i.e. panels that are always perpendicular

[1] Photovoltaic Software: `http://photovoltaic-software.com/PV-solar-energy-calculation.php`

to beams of the sun) can capture more energy during the whole year than the fixed panel [76]. We apply $Q = 0.75$ to the Quality Factor of the adjustable panel [76].

The number of photovoltaic panels installed for a prosumer is randomly selected between 4 and 22 at the beginning of the simulation. Then, we sum the production of each PV panel to obtain the total energy production of the whole installation.

In this simulation, the photovoltaic panel that we chose is LG315N1C-G4 (Product page accessed on 8 April, 2016): `http://www.lg-solar.com/global/products/index.jsp`) where $C_p = 0.192$, $A = 1.65$ and $P_{peak} = 315$.

To simulate the solar power, we got solar radiation data in 2015 of Eelde [2]. We obtained sunshine duration H (hour), global radiation G (J/m^2) and percentage of maximum potential sunshine duration $SP \in [0, 1]$. The time of sunrise and sunset in 2015 are taken from `www.timeanddate.com`. We selected time of sunrise and sunset in Groningen [5] which is about 10 km north of Eelde.

In the process of the simulation, we randomly selected one day D_r in a year and converted the current time slot to the hour T in the day. If T was out of the duration from sunrise to sunset, there was no sun light in T and the output of solar energy was 0. If T was in daylight hours, there was still a possibility of no sunshine in this hour (because of clouds). Therefore, we produced a random boolean value to indicate whether there was sunshine in T. The possibility of "true" for this value was SP. If it was "true", we used G with a random fluctuation of $\pm 20\%$ and H to calculate the solar energy production in T.

4.4.4 Simulation of Energy Consumption and Price

We simulate hourly electrical energy consumption of end-users based on the dataset provided by Liander [3]. This dataset records the hourly electricity consumption of small customers (connection $\leq 3 \times 25$ amperes) in the Netherlands in 2009. In the process of the simulation, we use the same day D_r as the wind energy production or solar energy production, and convert current time slot to the hour T in a day. Then, we obtain the value of average hourly consumption for an end-user from the dataset according to T and D_r. We adjust the value by a random fluctuation of $\pm 20\%$ as the hourly electrical energy consumption of this end-user.

We use three types of energy prices. One is a fixed tariff offered by the electric utility for selling its energy to consumers. We use €0.25 per kW·h since it was the tariff offered by Energiedirect.nl (`http://www.energiedirect.nl`) in 2015. This price includes taxes, grid fees, accounting risks, structuring of profiles, etc. Another type of price is also a fixed one, the one offered by the electric utility for buying energy from prosumers. In the Netherlands, this price ranges from €0.03 per kW·h to €0.1 per kW·h [1]. We use 0.065 per kW·h that is the middle value of this range. The last one is the real-time price decided by prosumers for selling their energy to consumers. At a time slot, a prosumer offers the same price to all consumers. When running at the next time slot, the same prosumer is able to offer energy at a new price. Price formation is beyond the scope of the present treatment. Thus we do not consider grid fees, accounting risks, structuring of profiles and taxes for the real-time price. We simply assume that, in order to be attractive for consumers, the prices offered by prosumers are lower than the fixed selling price of the electric utility. Moreover, these prices are higher than the fixed buying price of the electric utility. In the process of the simulation, we randomly generate a value in the range $[0.1, 0.2]$ for each prosumer at each time slot.

4.5 Evaluation and Discussion

4.5.1 Evaluation Cases

We consider three evaluation cases based on different power flow patterns. The first one is a *Radial-flow Case* that simulates the traditional energy distribution flow. Electrical energy goes from the electric utility (central provider) to all end-users in the test feeder. In this case, there are no prosumers. All end-users are consumers and all energy consumption in the test feeder is supplied by the electric utility. The electric utility injects energy into the test feeder via Node 650 of Figure 4.2. The energy is delivered to other end-users from this node. Node 650 is also an end-user but energy loss of delivering energy to this node is 0.

The second evaluation case is the *Optimal-flow Case*. It simulates the model and solution of the Smart Grid proposed in this chapter. Some of end-users are prosumers; energy production and peer-to-peer energy distribution are involved. The optimization strategy of peer-to-peer energy distribution in this case is that presented in Section 4.3.

The last case is the *Closest-flow Case*. It is based on the Optimal-flow Case with a minor adjustment to the power flow pattern. In this case, prosumers, energy production and peer-to-peer energy distribution are involved as the Optimal-flow Case. Though there is a difference in the optimization strategy. When finding the optimal providers in Algorithm 4, we select the providers that offer the lowest price without considering the cost of energy loss. These providers are the contract providers that actually receive the payments from the consumer. When planning power flows, we select the providers with the shortest distance to the consumer. These selected providers are the transit providers that actually transmit electrical energy to the consumer but they do not get any payment. The shortest distance means the minimum number of electric lines from a source node to a destination node. This power flow pattern is close to the realistic situation when transmitting electrical energy in the test feeder. Thus, the step of getting weight in Line 15 of Algorithm 2 is modified. We set the weight of each arc (u, adj) to 1 instead of R/V^2. The contract provider and the transit provider can be the same node or can be two different nodes. Therefore, it is possible that some providers are paid without exporting their energy and some providers export their energy without any payment.

4.5.2 Assessment Metrics, Baseline and Simulation Setting

To verify the effectiveness of the proposed solution, we design five assessment metrics. These are energy loss of delivery, energy provided by the electric utility, proportion of energy self-satisfaction in the test feeder, excess energy sent to the electric utility, and average energy costs per end-user. We use the Radial-flow Case (traditional power system) as a *baseline* to assess the other two evaluation cases.

To assess the influence of the prosumer, we set various number of prosumers for the Optimal-flow Case and the Closest-flow Case in the simulation. The number of prosumers is $M = 0, 1, 2, 3, 6, 10, 13$. This means that $0\%, 5\%, 10\%, 20\%, 50\%, 75\%, 100\%$ of the end-users are prosumers. When the number of prosumers is $M = 0$, the Optimal-flow Case and the Closest-flow Case equal the Radial-flow Case. For the Radial-flow Case, the number of prosumers is always 0 that dose not influence the simulation results.

In order to analyze simulation data, we run multiple instances of the simulation and calculate the mean values of all outputs for the metrics [78]. We set the number of simulation runs per configuration to $10,000$. That is, we run the simulation for $10,000$ days and calculate the mean values for all outputs of these days for each evaluation metric. In these $10,000$ days, each day is randomly selected from four seasons in a year. Therefore, the seasonal effects are considered in our simulation. In each iteration, each case runs once. Three evaluation cases share same generated data of energy consumption and energy prices offered by the electric utility. The Optimal-flow Case and the Closest-flow Case share the same generated data for energy production and energy prices offered by prosumers. In each iteration, the number of time slots is $T = 24$ and $\Delta t = 1$ h. To avoid conflicts between several consumers buying energy from one provider at the same time, the running of each end-user is isolated, independent and sequential. The sequence of running end-users is random at different time slots. But at the same time slot, the sequences of running end-users for three evaluation cases are the same.

4.5.3 Discussion

One aim of our study is to find strategies to decrease energy loss of delivery. The performance of energy loss reduction in the test feeder is shown in Figure 4.3. For the Optimal-flow Case and the Closest-flow Case, the overall trend of energy loss is decreasing with the increase of the number of prosumers. Energy loss in this figure is based on transmitting the same amount of energy in the three evaluation cases. For the Optimal-flow Case and the Closest-flow Case, the loss of buying energy from prosumers and the loss of buying energy from the electric utility are both counted. With the rising number of prosumers, the amount of energy transmitted from the electric utility decreases (Figure 4.5) and the amount of power flowing as the proposed solution increases. Then, the efficiency of energy loss reduction in the test feeder is improved. This finding means that the solution proposed in this chapter outperforms the baseline (traditional power system) in reducing energy loss of delivery.

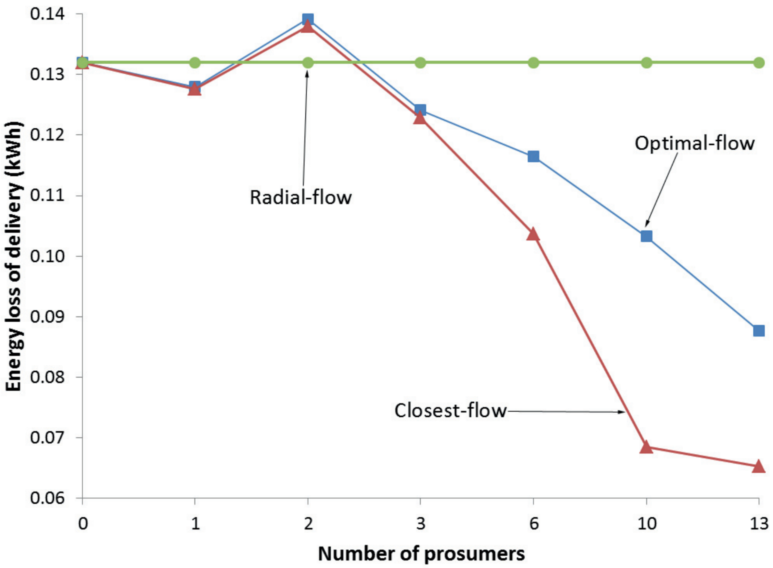


Figure 4.3: Energy loss of delivery in the test feeder.

In Figure 4.3, there are peaks of energy loss for both the Optimal-flow Case and the Closest-flow Case and the peaks are beyond the baseline. This happens when the number of prosumers, denoted by M, is 2. This can be explained with the consumers' preference to buy energy from prosumers in our simulation. Consumers still would buy energy from prosumers when the energy loss of buying energy from prosumers is greater than the cost of buying energy from the electric utility. When $M = 2$, the influence of the case mentioned above is significant. This can cause the increase of energy loss. For example, if we assume that the prosumers are Node 634 and Node 646, and one of consumers is Node 611; that energy from the electric utility is injected via Node 650, then for Node 611, buying energy from Node 634 or Node 646 obviously has more energy losses than from the electric utility. When $M = 1$, there is only about 12% of energy in the test feeder provided by the prosumer (shown in Figure 4.4). Compared to 50% of energy provided by the prosumers when $M = 2$, the influence of the case mentioned above is limited. When $M \geq 3$, there are more choices for consumers to select prosumers. Therefore, the consumers are able to buy energy from the prosumers with lower energy loss than when $M = 2$.

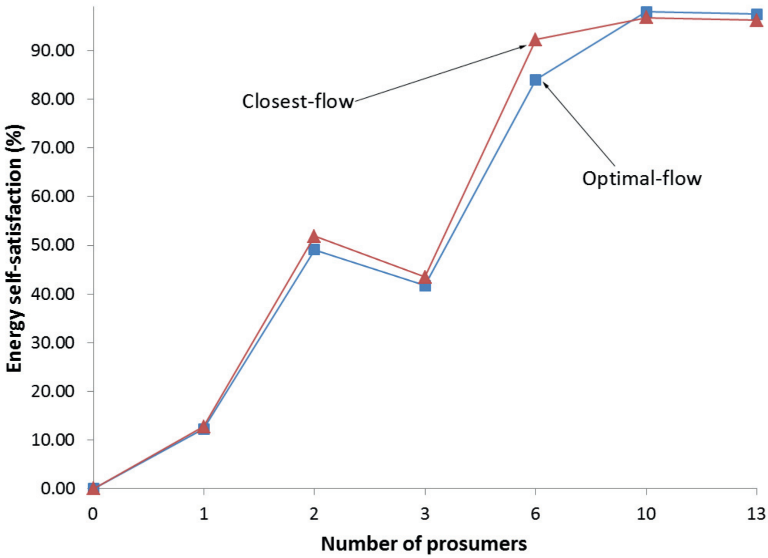


Figure 4.4: Proportion of energy self-satisfaction.

Comparing to the traditional power system, the Smart Grid has a considerable advantage in terms of improving independence from centralized energy generation and central energy providers. The upward trend in proportion of energy self-satisfaction is shown in Figure 4.4. The proportion of energy provided by prosumers to the total energy consumption increases with the rising number of prosumers in both cases of the Optimal-flow and the Closest-flow. In fact, the increasing number of prosumers causes the increase of distributed energy generation and peer-to-peer energy distribution among end-users. For the Radial-flow Case (i.e., baseline), the energy self-satisfaction is always 0, overlapping with the X axis. On the contrary, energy provided by the electric utility decreases when we add prosumers. This can be observed in Figure 4.5.

The reason of this descending trend is the same as the reason of the ascending trend of energy self-satisfaction. Moreover, the results of the Optimal-flow Case and the Closest-flow Case are lower than the baseline. This finding supports that the solution improves independence from centralized energy generation and central energy providers.

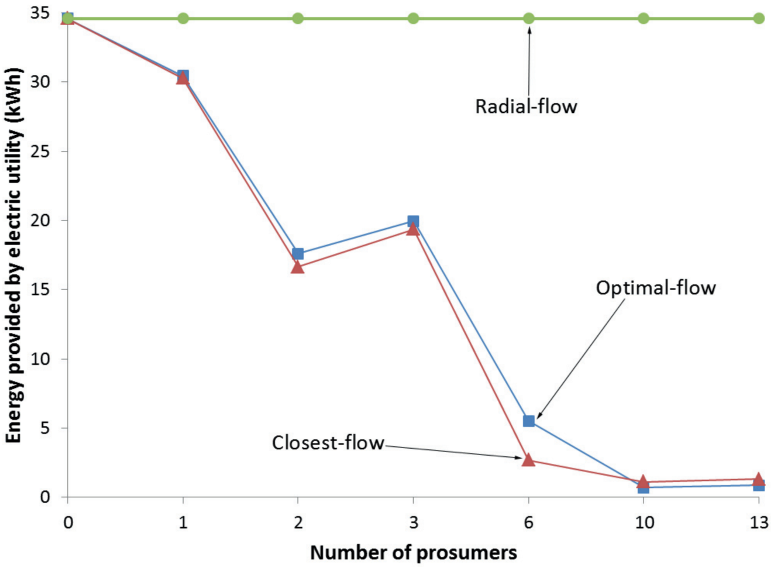


Figure 4.5: Energy provided by the electric utility.

We also measure the excess energy that is sent to the electric utility. The excess energy shown in Figure 4.6 is prosumers' energy that is not sold or transmitted to other end-users. For the Radial-flow Case (i.e., baseline), the excess energy is always 0, overlapping with the X axis. For other two cases, it significantly increases with the number of prosumers. The reason of this ascending trend is similar to the one of energy self-satisfaction. However, most parts of the two curves in Figure 4.6 overlap. In other words, different patterns of power flows have no influence on this metric.

Another aim of our study is to save energy costs for end-users. The energy cost is the total amount of money paid by the end-user for buying energy over a day. The results in Figure 4.7 show a dropping trend of the average energy costs per end-user with the rising number of prosumers. The results of the Optimal-flow Case and the Closest-flow Case are both lower than the baseline. Since the price formation is beyond the scope of our study, we simply consider that the renewable energy produced by prosumers has different prices from the energy provided by the electric utility;

grid fees, accounting risks, structuring of profiles and taxes are considered to be fixed. Thus, renewable energy produced by prosumers is sold with lower price than energy provided by the electric utility in the Smart Grid. Increasing the number of prosumers can increase the amount of renewable energy sold at low price, and can increase the availability of peer-to-peer energy distribution to reduce energy losses paid by end-users. Therefore, energy costs of end-users are lower when more prosumers are involved in the test feeder and more renewable energy is exchanged among end-users.

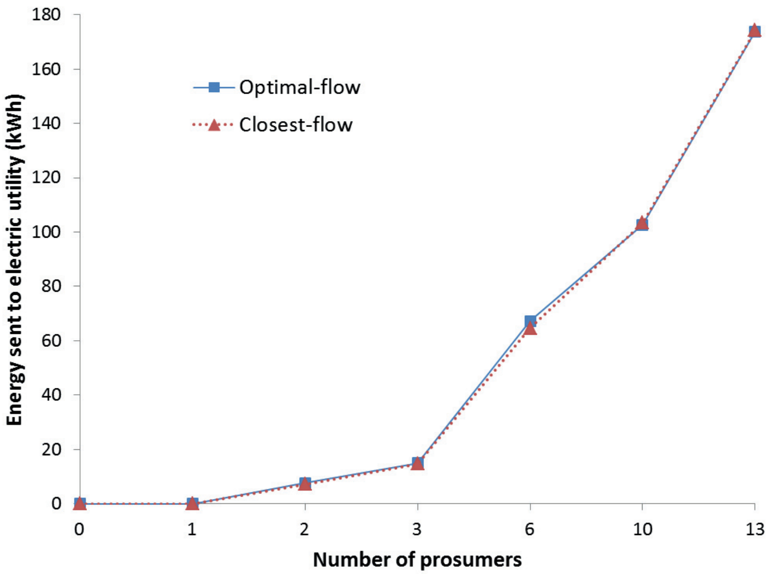


Figure 4.6: Excess energy sent to the electric utility.

The figures give an indication of the overall performance of the Optimal-flow Case and the Closest-flow Case and how these significantly improve on the current baseline (i.e., the Radial-flow Case). To clearly indicate the improvement, numerical data of the evaluation based on four metrics are shown in Table 4.2. We calculate the percentage of the maximum reduction based on the baseline for three metrics, including energy loss of delivery, average energy costs and energy provided by the electric utility. The maximum values of energy self-satisfaction proportion are also shown. Compared to the baseline, the maximum reduction of energy loss is 51%, achieved by the Closest-flow Case. The Optimal-flow Case maximumly reduces energy provided by the electric utility by 97.5%. It also obtains the maximum proportion of energy self-satisfaction that is 98%. The maximum reduction of average energy costs per end-user is 66% achieved in both cases.

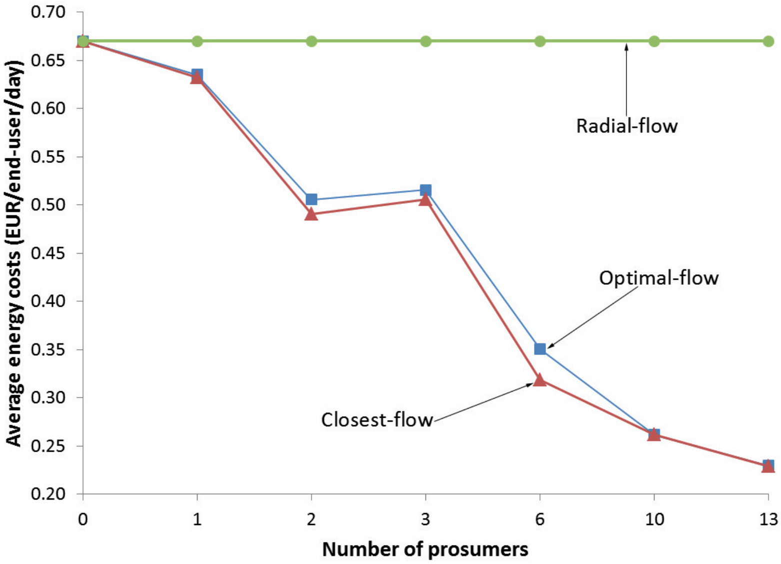


Figure 4.7: Average energy costs per end-user per day.

To compare the Optimal-flow Case with the Closest-flow Case, based to the data in Table 4.2, we provide Figure 4.8. The figure highlights how these two evaluation cases have the same performance in the maximum reduction of average energy costs per end-user. They also have very close performance in the maximum reduction of energy provided by the electric utility and the maximum proportion of energy self-satisfaction. However, the Optimal-flow Case slightly exceeds the Closest-flow Case in these two metrics. On the other hand, the Closest-flow Case significantly outperforms the Optimal-flow Case in energy loss of delivery.

Table 4.2: Performance comparison with the evaluation cases.

Assessment Metrics	**Radial-Flow**	**Optimal-Flow**	**Closest-Flow**
	Baseline	Maximum reduced	Maximum reduced
Energy loss of delivery	0.13 kW·h	33%	51%
Average energy costs	0.67 EUR	66%	66%
Energy from electric utility	34.6 kW·h	97.5%	96%
	Baseline	Maximum proportion	Maximum proportion
Energy self-satisfaction	0	98%	96.8%

For energy loss of delivery, the Closest-flow Case obviously outperforms the Optimal-flow Case (Figure 4.3 and 4.8). The reason of this outcome is linked to the use of a radial test feeder to test the solution. As described in Section 4.5.1, the power flow pattern of the Closest-flow Case approximates to the realistic situation when delivering energy in the test feeder. In the realistic situation, the test feeder has the radial topology. Thus, the Closest-flow Case is designed for the radial test feeder. It may therefore have better performance than the Optimal-flow Case in this test feeder. However, the ideal test platform for the Optimal-flow Case is a test feeder with a more meshed topology. In the radial network, there is only one path between each pair of nodes. This negatively influences the optimization of delivery paths proposed in Section 4.3.3. For example, if in Figure 4.2 Node 634 transmits energy to Node 611, the power flow travels on the longest path in the test feeder and blocks energy transit between other nodes. The blocked consumers have to buy energy from the electric utility. This may increase energy loss of delivery. When the number of prosumers rises, the number of nodes involved in peer-to-peer energy distribution increases. Then, the negative influence of the radial topology may therefore become apparent.

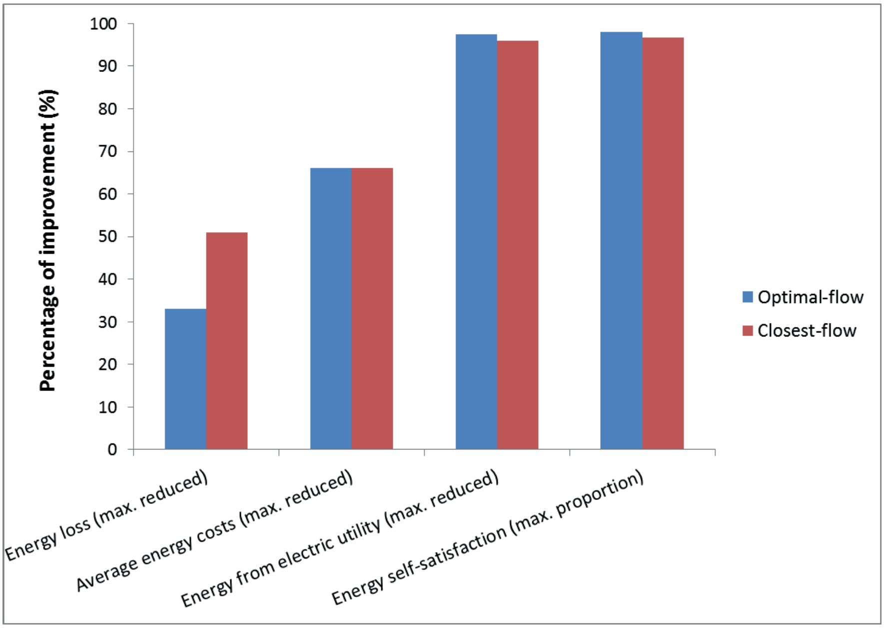


Figure 4.8: Comparison with assessment metrics of Optimal-flow Case and Closest-flow Case.

4.6 Summary

In this chapter, we proposed a novel strategy for optimizing the route of peer-to-peer energy distribution based on the Smart Grid. The optimization strategy considers renewable energy production of prosumers, energy loss of delivery, topology of the distribution network, and physical constraints including ampacity of electric lines and directions of power flows. A mathematical model of the optimization problem and a peer-to-peer model of the Smart Grid are central to the present study. We design algorithms and evaluate them by building a simulation program and running it on three representative cases. The simulation results prove the effectiveness of our solution. Compared with the traditional power system, the maximum reduction of energy loss, energy costs, and energy provided by the electric utility based on the proposed solution can achieve 51%, 66%, and 97.5%, in each case. Besides, the maximum proportion of energy self-satisfaction in the test feeder approaches 98% and there is large amount of excess energy sent to the electric utility. The study does provide further evidence to the potential of having an open energy market for prosumers, as this is more efficient and it makes become a prosumer economically more attractive than the current model where the utilities buy back the produced energy. The proposed algorithms are based on heuristic methods. The final results provided by our solution are near-optimal.

Chapter 5

Topological Considerations on Peer-to-peer Energy Distribution

The Smart Grid provides two significant advantages: reducing the dependence on non-renewable resources (e.g., fossil fuels); and enhancing the independence from centralized energy production, supply and operation. The distribution network is formed from the low and medium voltage (LV and MV) grids including transformers and substations. The term “local scale” identifies as a residential area covered by a part of the distribution network working at LV without substations and transformers. In this context, the research problem addressed in this chapter is about which topology models are more appropriate to support decentralized energy exchange at a local scale and how the topological models affect the decentralized energy exchange?

This chapter extends the results of Chapter 4 and investigates the topological effects on the optimization of energy distribution, that is, to study how the topology of distribution grids affect the optimal distribution of energy at the local scale. The work presented goes beyond the statistical approaches from traditional Complex Network Analysis (CNA) and adds details of power flow routing. The proposed model finds a balance between purely topological/statistical ones and traditional precise power engineering ones. In addition, this chapter provides an analysis of distribution network topologies on the basis of a quantitative approach based on simulations.

5.1 Monte Carlo Simulation

To understand the optimization strategy’s effectiveness and its dependence on the various parameters, we resort to stochastic simulations. In particular, the Monte Carlo Simulation method relies on generating repeated random numbers [77, 110]. In our work, this entails the use of statistical distributions for modeling energy consumption, renewable energy production, and real-time pricing. We run simulations for several topological models, to assess the topological effects on the optimization of energy distribution. In particular, we consider: a small-world model [137], a random graph model [101], a complete graph model, and a radial model. The reason for choosing the small-world model is that this model obtains a good balance between the upgrading costs for infrastructure and energy distribution efficiency [106]. The other models are considered as they form a benchmark for comparison. The radial model is the currently most common network distribution model used in practice and thus can be considered a comparison with current practice. While the random graph and the complete graph models can be seen as extreme cases of the small-world models where the rewiring probability is maximum or null, respectively. Next, we illustrate the specific sub-models for energy production, consumption, and distribution networks.

5.1.1 Simulation of Wind Energy Production

Small wind turbines and photovoltaic panels are the typical small-scale energy generators adopted by prosumers. We associate to each prosumer randomly either a wind or solar generator. Wind power is dependent on the rotor blade length of the turbine, wind speed and air density. For the formulas of generating wind power P_w (Watt) and calculating electrical energy E_w (Joule), we refer to Equation (4.14) in Chapter 4. The analytical correlation between the wind speed V (m/s) and the generated wind power P_w depends on the control characteristics of the wind turbine, which are the speed of cut-in V_{ci} and the speed of cut-off V_{co}. A wind turbine only works when the wind speed is in $[V_{ci}, V_{co}]$. Otherwise, the turbine is locked. Meaning that $P_w = 0$ when $V < V_{ci}$ or $V > V_{co}$.

We apply a standard three-bladed turbine [24] in the simulation, where the swept area of blades $A = 10.75$ (m^2), the maximum power output $P_{max} = 2600$ (Watt), $V_{ci} = 2$ (m/s), and $V_{co} = 13$ (m/s). We approximate the wind turbine's efficiency C_w from the efficiency curve, as shown in Figure 5.1. For air density, we use the average value $\rho = 1.225$ (kg/m^3) [56].

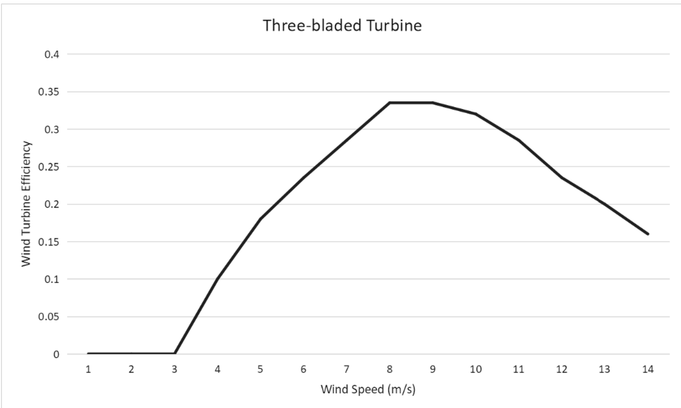


Figure 5.1: Three-bladed efficiency curve of the wind turbine, from [24].

The wind speed is generated by applying a Weibull distribution [63]. The scale and shape of the distribution are calibrated by means of historical measures. In [17], the author calculates the parameters of the Weibull distribution for 97 sites in Italy based on wind data collected throughout the country during 30 years. We use Milano Malpensa site's data provided by this work, in which the scale is 3.18 and the shape is 1.4 [17]. This site is located near an international airport. Therefore, the wind data of this site are more stable and can provide useful information of wider validity [17].

5.1.2 Simulation of Solar Energy Production

For the photovoltaic panel simulation, we consider one hour intervals and the temperature, air pressure, local time, and geographical location. For a cloudy sky, the model of hourly solar radiation is on the basis of the widely adopted model from [120]. The model is characterized by the peak solar radiance $S_{max,t}$ (kW/m^2), the sunrise t_{rise} and sunset t_{set} times. More precisely:

$$\begin{cases} I_{ss,t} = 0, t \leq t_{rise} \\ I_{ss,t} = S_{max,t} \cdot sin \, \dfrac{\pi \cdot (t - t_{rise})}{t_{set} - t_{rise}} \\ I_{ss,t} = 0, t \geq t_{set} \end{cases} \tag{5.1}$$

where $I_{ss,t}$ is the solar radiance (kW/m^2) of the simple sky model at time t, t_{rise} and t_{set} are the sunrise and sunset time, respectively. In the present work, as the panels are assumed to be roof-based, $S_{max,t}$ is the maximum terrestrial radiance in an hour $I_{ETI,max,t}$ multiplied by the hourly clearness index CI_t. $I_{ETI,max,t}$ is dependent on the zenith angle $\theta_{Z,t}$, eccentricity factor E_0, and the peak value on terrestrial surface I_0, shown below [120]:

$$\begin{cases} S_{max} = I_{ETI,max,t} \cdot CI_t \\ I_{ETI} = I_0 \cdot E_0 \cdot cos\theta_{Z,t} = 1362 \cdot 1 + 0.033 \cdot cos \, \dfrac{2 \cdot \pi \cdot d_n}{365} \, \cdot cos\theta_Z \end{cases} \tag{5.2}$$

where d_n is how many days simulated in a year. The angle between the sun position and vertical axis is called the zenith angle (Z) $\theta_{Z,t}$. To calculate $\theta_{Z,t}$, we refer to [44] where five algorithms for the calculation are presented. We choose the Algorithm 3 because it has the best balance between model precision and computational costs.

Algorithm 3 depends on the temperature, air pressure, local time, and geographical location. For the geographical location, we choose Maastricht in The Netherlands as detailed weather data is available thanks to the Royal Netherlands Meteorological Institute (KNMI) [2]. Furthermore, Maastricht is the least influenced city of the Netherlands with respect to North Sea weather fluctuations. The data includes daily average cloud coverage, daily minimum temperature, daily maximum temperature, lowest hourly value of air pressure, and highest hourly value of air pressure. We use the meteorological data of 2016, where the sunrise and sunset times are obtained from "`www.timeanddate.com`".

In a year, we select a random day d_n and the hour t in d_n is the time slot. When t is not in the sunrise to sunset interval, the energy output is null. Otherwise, we use the weather data of the day and generate random numbers to calculate solar radiation and solar energy production in t. The value of the air pressure at t is randomly generated between the minimum and maximum values of the air pressure in a day. For the temperature, we assume that the hourly temperature T_t is linear between the minimum temperature T_{min} at the time H_{Tmin} and maximum temperature T_{max} at H_{Tmax} in a day. Then, we can estimate the temperature at time t by linear functions as follows:

$$\begin{cases} T_t = \dfrac{(T_{max} - T_{min}) \cdot (t - H_{Tmin})}{H_{Tmax} - H_{Tmin}} + T_{min} \ , t \in [H_{Tmin}, H_{Tmax}], H_{Tmin} < H_{max} \\ T_t = \dfrac{(T_{min} - T_{max}) \cdot (t - H_{Tmax})}{H_{Tmin} - H_{Tmax}} + T_{max} \ , t \in (H_{Tmax}, H_{Tmin}), H_{Tmax} < H_{Tmin} \\ T_t = 0, other \end{cases} \tag{5.3}$$

when the time t is not in $[T_{min}, T_{max}]$, we generate a random number in $[T_{min}, T_{max}]$ as T_t.

For a cloudy sky, the clearness index CI_t is the sky portion that is without cloud covering. CI_t is generated by a normal distribution whose mean value is in $[0.4476, 0.64811]$ and standard deviation of 0.14 [60]. The mean value of CI_t varies daily and the seasonal variability is taken into account. We transform the daily average cloud coverage CC_d into the mean value of the clearness index in a day by $1 - CC_d/CC_{upper}$, where CC_{upper} is the upper bound of CC_d. For generating electrical energy E_s and solar power P_s via photovoltaic panels, we refer to Equation (4.15) in Chapter 4.

We choose LG360Q1C[1] as the simulated photovoltaic panel where the photovoltaic panel's efficiency $C_p = 0.196$, the photovoltaic panel's surface area $A = 1.73$ (m^2) and the photovoltaic panel's peak power output $P_{peak} = 360$ (Watt). Because it has the top-three highest quality in 2017 and affordable price for the residential users[2].

For residence buildings, fixed or adjustable panels are realistic choices. We assume that all photovoltaic panels are adjustable panels and their tilt is adjusted twice a year: in the summer and winter. Because adjustable panels can capture more energy during the whole year than fixed panels [76]. The Quality Factor (Performance Ratio)

[1] Product page (accessed on 30 December 2017): `www.lgenergy.com.au/products/solar-panels/lg-neon-r-r/lg360q1c`

[2] `https://www.ohmhomenow.com/best-solar-panel-brands/`

of the adjustable panel is $Q = 0.75$ [76].

In the Netherlands, a residential building typically has 4 to 6 photovoltaic panels [130]. In relevant rare cases, some buildings do not have sufficient roof areas to fit 4 panels and some buildings have relevant higher energy consumption requiring more than 6 panels. Therefore, we consider that an end-user installs 2 to 8 panels. Since the photovoltaic panels are usually installed with even numbers, we randomly select a number in $\{2, 4, 6, 8\}$ for a prosumer when the simulation starts. The total energy generated by the whole installation is the sum of the generation of each photovoltaic panel.

5.1.3 Simulation of Energy Consumption

Studies on the household energy consumption profile exist. Ogunjuyigbe *et al.* provide the profile of a typical household [103]. In [42], a similar profile is identified. Both of these profiles have two consumption peaks. One is in the afternoon and another one is in the morning. Therefore, the consumption in an hour of end-users can be assumed to be drawn by a bimodal distribution [39].

The bimodal distribution has two normal distribution curves combined that can model the two consumption peaks during one day. Then, we assume the boundary of the bimodal distribution to be at 11:00AM. Therefore, one peak appears in the morning around 6:00AM, and the other one is in the afternoon around 5:00PM. The bimodal distribution's parameters are calculated via the dataset of Liander [4]. In the afternoon, the standard deviation and mean of the consumption are 0.064 and 0.227, respectively. In the morning, the standard deviation and mean of the consumption are 0.058 and 0.15, respectively.

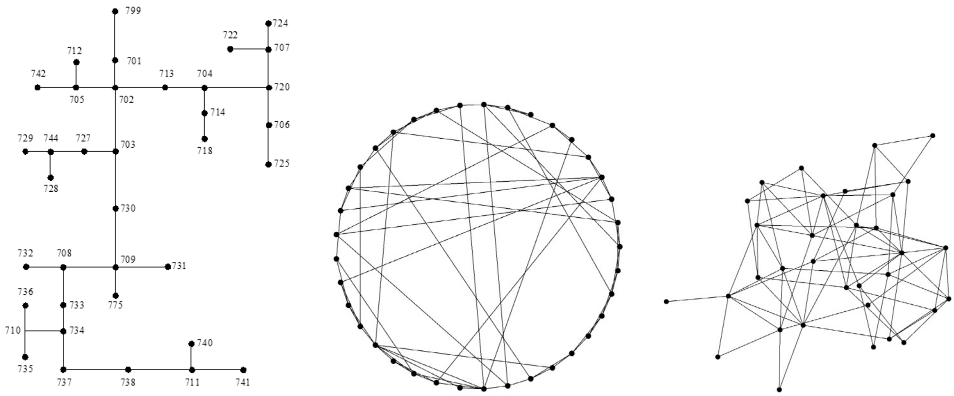
5.1.4 Simulation of Energy Prices

The energy price is assumed to change every hour and to correlate to overall country demand. It therefore follows the bimodal distribution of energy consumption with the same boundary. The parameters of such energy price distribution are coherent with the "electricity price statistics"[3] in 2017. The mean value of the distribution is €0.2 per kW·h which is the average price for the European 28 countries ("EU-28"). The standard deviation of the distribution is 0.05. The minimum price is €0.05 per kW·h. The electric utility offers a fixed price that is set to €0.22 per kW·h, which is the average price of "Euro area".

[3] `http://ec.europa.eu/eurostat/statistics-explained/index.php/Electricity_price_statistics`

5.1.5 Simulation of Distribution Networks

A standard three-phase IEEE distribution test feeder is used to represent the radial topologies [64]. The network consisting of 37 nodes is adapted for the simulation by removing the transformer and regulator, by considering a voltage of 120V for all electric lines (Figure 5.2(a)). All of 37 nodes in the test feeder are assumed to be end-users and the distributed loads of three phases are assumed to be balanced. To generate small-world (Figure 5.2(b)) and random graph (Figure 5.2(c)) models, we use the Java library "GraphStream"[4]. Each electric line in all topologies has the same material and equal length. Thus, all electric lines have equal electrical resistance and amapcity.



(a) Radial test feeder with 37 nodes. (b) Graph of the small-world model with 37 nodes. (c) Random graph with 37 nodes.

Figure 5.2: A test feeder and graphs of topology models.

5.2 Simulation Execution and Results

We build a Java program to implement the Monte Carlo simulations of the model presented in Section 5.1. The simulation program is run on the Peregrine High Performenace Computing cluster[5] with 24 cores at 2.5 GHz and 112 GB memory. The running of this program approximately consumes 139 hours.

[4] `http://graphstream-project.org`

[5] Peregrine HPC cluster: `www.rug.nl/society-business/centre-for-information-technology/research/services/hpc/facilities/peregrine-hpc-cluster`

5.2.1 Assessment Metrics

We design four metrics to evaluate the topological effects on the optimization strategies. The metrics are populated using the same load demand satisfaction. Firstly, to assess the energy delivery efficiency, we measure the energy loss ratio in the distribution network. The measured energy losses are on the basis of transferring the equal amount of energy in various considered topologies. For any end-user, the losses based on transferring energy from prosumers and from the super agent are both accounted for. $LOSS_{t,i}$ denotes the energy loss of an end-user $eu_{t,i}$ at Δt. $BUY_{t,i}$ denotes the amount of energy that an end-user $eu_{t,i}$ buys at Δt. We measure the ratio between energy losses on the network and the amount of energy that all end-users buy over a day (Equation (5.4)).

$$\frac{\sum\limits_{\forall t \in |T|} \sum\limits_{\forall eu_{t,i} \in |EU|} LOSS_{t,i}}{\sum\limits_{\forall t \in |T|} \sum\limits_{\forall eu_{t,i} \in |EU|} BUY_{t,i}} \tag{5.4}$$

Secondly, to evaluate the economic benefits of a particular topology, we measure the energy costs for end-users. The energy costs are the total money that the end-users pay for buying and delivering energy from both prosumers and the super agent. $COST_{t,i}$ denotes the energy cost of an end-user $eu_{t,i}$ at Δt. We measure the energy cost (unit: EUR) of buying and delivering 1 kW·h energy on the network (Equation (5.5)).

$$\frac{\sum\limits_{\forall t \in |T|} \sum\limits_{\forall eu_{t,i} \in |EU|} COST_{t,i}}{\sum\limits_{\forall t \in |T|} \sum\limits_{\forall eu_{t,i} \in |EU|} BUY_{t,i}} \tag{5.5}$$

Thirdly, to evaluate the influence on energy distribution flows we measure the maximum load in distribution networks. The maximum load in an electric line is the maximum energy an electric line carries at a time slot. We measure the maximum load (unit: kW) of the distribution network which is the maximum value of the loads in all electric lines in the whole network over one day. The electric line set is E and the load in an electric line $e_{t,i}$ at Δt is denoted by $LOAD_{t,i}$. Then, we have Equation (5.6).

$$\max_{\forall t \in |T|} \{ \max_{\forall e_i \in |E|} LOAD_{t,i} \} \tag{5.6}$$

Lastly, we measure the average delivery path length for energy distribution in order to assess the efficiency of transmitting electricity between two nodes. The average delivery path length is the average hop count of all delivery paths from all resources (providers) to all destinations (consumers) in the distribution network. It represents the average number of electric lines of the delivery paths to transfer energy from providers to users who buy the energy. Since each electric line in all topologies has the same length and electrical properties, each electric line in all topologies has the same weight. Hence, the delivery path length equals the weighted delivery path length. $DPL_{t,i}$ denotes the total delivery path length for transferring all bought energy to an end-user $eu_{t,i}$ at Δt. $DPN_{t,i}$ denotes the number of delivery paths for transferring all bought energy to an end-user $eu_{t,i}$ at Δt. Then, we measure the average delivery path length (unit: step) to transfer all bought energy by all end-users over a day (Equation (5.7)).

$$\frac{\sum\limits_{\forall t \in |T|} \sum\limits_{\forall eu_{t,i} \in |EU|} DPL_{t,i}}{\sum\limits_{\forall t \in |T|} \sum\limits_{\forall eu_{t,i} \in |EU|} DPN_{t,i}} \tag{5.7}$$

5.2.2 Power Flow Patterns

We apply two patterns of the power flow. One is Radial-flow that simulates energy distribution flows in the traditional way. In the distribution network, all end-users get energy from a central provider. The prosumer is not part of this pattern. The central provider injects electrical energy into the distribution network via Node 799, as shown in Figure 5.2(a). The second pattern is the Optimal-flow one that adheres to the model proposed in Section 4.2 in Chapter 4. In this model, some or all of the end-users act as prosumers; energy production, real-time energy price, and peer-to-peer energy exchange are enabled. We refer to Section 4.3 in Chapter 4 for the algorithms of the Optimal-flow.

5.2.3 Evaluation Stages and Prosumer Settings

We divide the evaluation process into two stages. In the first stage, we compare the performance based on various topologies. We test the random graph, complete graph, radial and small-world models. For the small-world model, we use a rewiring probability $p = 0.4$ and an average degree of four $k = 4$, which provide a good balance between energy distribution efficiency and the cost of upgrading the infrastructure [106]. Then, we use the same average degree $k = 4$ for the random graph model. The experiments are performed on the modified IEEE 37-node test feeder, introduced in Section 5.1.5. To model the traditional distribution way, we apply the Radial-flow pattern introduced in Section 5.2.2 to the radial topology. We apply the Optimal-flow to all topologies. This leads to five evaluation cases: “Traditional”, “Complete Graph”, “Small-world”, “Random Graph”, and “Radial”. We apply the Traditional to the baseline. We use several settings of the prosumer for the Optimal-flow cases with the goal to understand the influence of the number of prosumers. The case considers 24%, 50%, 75%, and 100% of prosumers; more precisely $M = 9, 18, 27, 37$ in the 37 nodes networks. These settings are referred to as "24%-prosumer", "48%-prosumer", "73%-prosumer" and "100%-prosumer", respectively. For the baseline (i.e., evaluation case Traditional), the number of prosumers is always 0 and it is therefore referred to as "0%-prosumer".

In the second stage, we test small-world and random graph by varying graph formation probabilities by small increments. More precisely, the tested parameters of the random graph model are average degrees $k = 4, 6, 8, 10, 12$, while for the small-world model we test the same average degrees as the random graph model and $p = 0.2, 0.4, 0.6, 0.8, 1.0$ as the rewiring probabilities. We repeat the experiments for the 100 node graphs. The evaluation cases are named with the acronyms of topology models. For example, the random graph with $k = 4$ is referred to as "RG4" and the small-world having $k = 4, p = 0.4$ is referred to as "SW44".

In the second stage, we go beyond the traditional distribution way. Therefore, only the Optimal-flow pattern is applied and the Traditional case is not part of the simulation. We only compare the Random Graph case and the Small-world case with each other. We also assume that all end-users are prosumers, since the evaluation in this stage focuses on the topologies. Hence, this stage only has one prosumer setting, $M = 100$. In addition, this stage has the same physical constrains of distribution networks as the first stage. Meaning that the voltage for all electric lines is 120V, and all phases have the balanced loads, and each electric line has the same electrical resistance and amapcity.

5.2.4 Simulation Settings

The Monte Carlo approach is based on running many several simulation instances and processing the statistics of all outputs [78]. Thus, in the first stage, we run the simulation $10,000$ times. Meaning that the program simulates $10,000$ days and calculates the mean values of the simulation outputs. The simulation randomly selects each day from the four seasons. Hence, the simulation represents the seasonal effects. In the second stage, the number of simulated days is set to $5,000$. Because the computation time of simulating more than $5,000$ days is too long to be accepted by the HPC cluster. Each evaluation case runs once in each iteration. In any iteration, $\Delta t = 1$ hour and there are $T = 24$ time slots.

5.2.5 Results

The results of the simulation are intended to determine whether the topology has an impact on the efficiency of open peer-to-peer energy market and, if it does, what models perform best. First we consider the various topological models, and then we analyze the effects of parameter tuning for the most promising ones.

Topology Comparison

First, we assess the energy loss ratio. That is, the total amount of energy losses in the distribution network divided by the total amount of energy bought by all end-users (see Equation (5.4)). This metric indicates the performance of energy loss reduction for delivering energy in the distribution network. The measured energy losses are based on transferring a given, fixed amount of energy in the evaluated topologies, including the losses of transferring energy from prosumers and from the super agent. The simulation results are shown in Figure 5.3, where the Complete Graph, Small-world, Random Graph and Radial have decreasing energy loss with the increasing number of prosumers. The decrease of performance for these topologies are approximately linear. The energy loss maximally decreases 23%, compared to the baseline, achieved by the Complete Graph when the percentage of the number of prosumers reaches 100%. The Complete Graph performs better than other topology models in all prosumer settings. The Random Graph ranks second. Its performance is less than the performance of the Complete Graph by 4.3% at 24%-prosumer, by 5.7% at 100%-prosumer and by 6.5% at other two prosumer settings. The performance of the Small-world only has 0.7% less than the performance of the Random Graph at 73%-prosumer. Using three different prosumer settings, these two topology models have the same performance. The Radial ranks last. Its performance is less than the performance of the Small-world by 2.9%, 4.3%, 4.3% and 4.4% at four prosumer settings respectively.

Second, we evaluate the energy costs for end-users which include the cost of buying energy and the cost of transferring energy. The costs are the money paid by the end-users for buying and delivering one Kilowatt-hour on the network (see Equation (5.5)). This metric indicates the performance of energy cost reduction in various topology models. As one can see in Figure 5.4, the Complete Graph, Small-world, Random Graph and Radial have decreasing energy cost with the increasing number of prosumers. The decrease for the topologies are almost linear. The energy cost maximally decreases 8%, compared to the baseline, achieved by the Complete Graph when the prosumer percentage reaches 100%. The Small-world ranks second followed by the Random Graph and the Radial is the last one. However, with the same prosumer setting, the performances of different topologies have small differences. The performance of

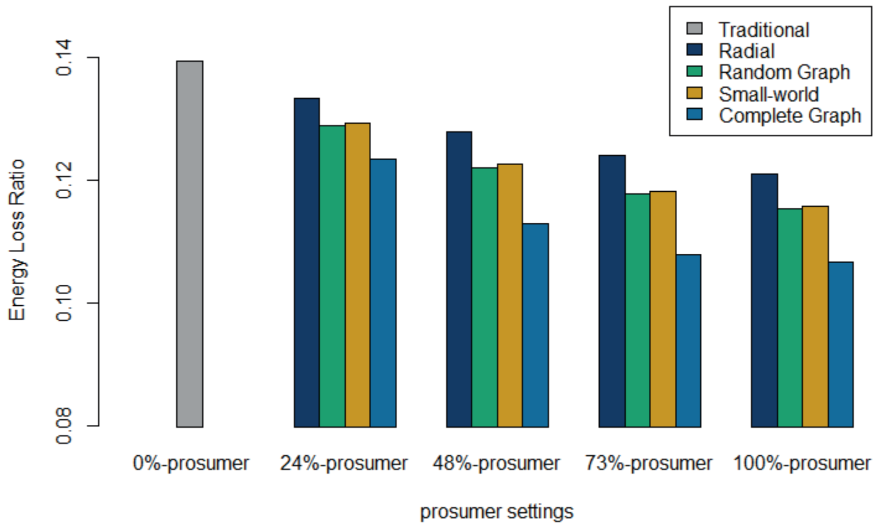


Figure 5.3: Energy loss ratio.

the Small-world is less than the performance of the Complete Graph by 0.4% at all prosumer settings. However it exceeds the performance of the Random Graph by 0.4% at 73%-prosumer and 100%-prosumer. The Random Graph has the same performance with the Small-world at 24%-prosumer and 48%-prosumer. The performance of the Radial is less than the performance of the Random Graph by 0.8% at all prosumer settings.

Then, we evaluate the maximum load in the distribution network. The simulation results are shown in Figure 5.5, where the Complete Graph, Small-world, Random Graph and Radial have meaningful reductions compared to the baseline. The Complete Graph performs better than other topologies in all prosumer settings. It achieves the maximum reduction of 96.3% when the prosumer percentage is 100%. The Small-world ranks second. Its performance reaches 88.7% at 100%-prosumer, which is less than the performance of the Complete Graph by 7.6%. The performance of the Random Graph is almost same as the performance of the Small-world. The performance difference between these two topologies is no more than 0.2%. The Radial ranks last. Its performance is less than the performance of the Random Graph by 9.6%, 11.6%, 10.9% and 9.3% at four prosumer settings respectively. Furthermore, for all topologies, more prosumers only have slight influence.

Lastly, we evaluate the average delivery path length for delivering energy and show the simulation results in Figure 5.6. As one can see, the performances of four prosumer settings are very close for all topologies. The average delivery path length

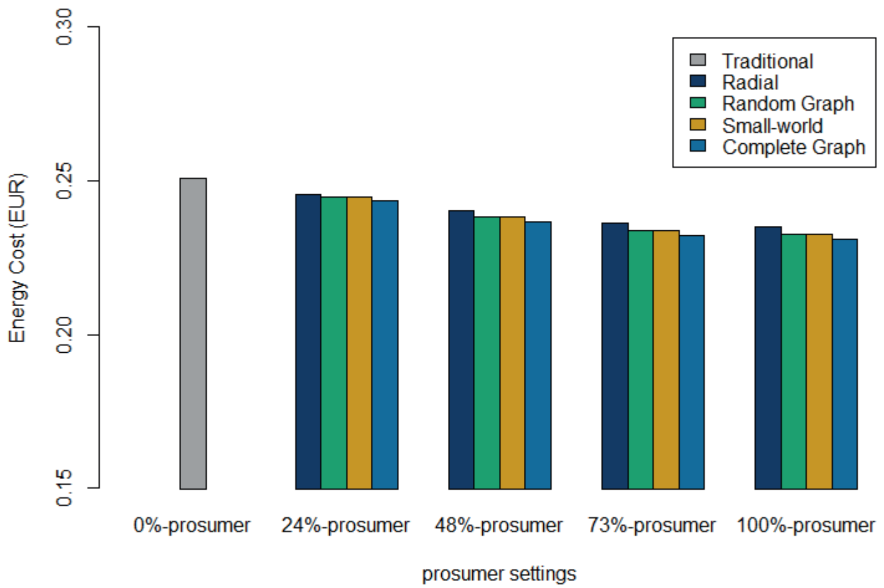


Figure 5.4: Energy costs for end-users.

maximally decreases with a value of 84%, compared to the baseline, achieved by the Complete Graph at all prosumer settings. The Random Graph ranks second. Its maximum reduction for this metric reaches 56.1% at 73%-prosumer and 100%-prosumer, which is less than the performance of the Complete Graph by 27.9%. The Small-world ranks third. It has close performance to the Random Graph. The maximum performance difference between these two topologies is 2.7% at 48%-prosumer and 73%-prosumer. The Radial ranks last. The performance of the Small-world exceeds the performance of the Radial from 23.1% to 30.3% which means a relevant large performance enhancement.

The figures provide an overall illustration of the assessment metrics' performance. To show the enhancement clearly, assessment numerical data are also provided. Thus, the reduction percentage compared to the baseline for each metric is calculated, as shown in Table 5.1. The energy loss ratio, maximum load, energy cost and average delivery path length maximally decrease 23%, 96.3%, 8% and 84%, respectively, achieved by the Complete Graph. The Radial has the bottom performances for all metrics. Comparing the Small-world and Random Graph, they have the same maximum reduction of energy loss ratio which is 17.3%. The Small-world performs better than the Random Graph at energy cost and maximum load with the maximum reduction 7.6% and 88.7% respectively. However, the Random Graph exceeds the

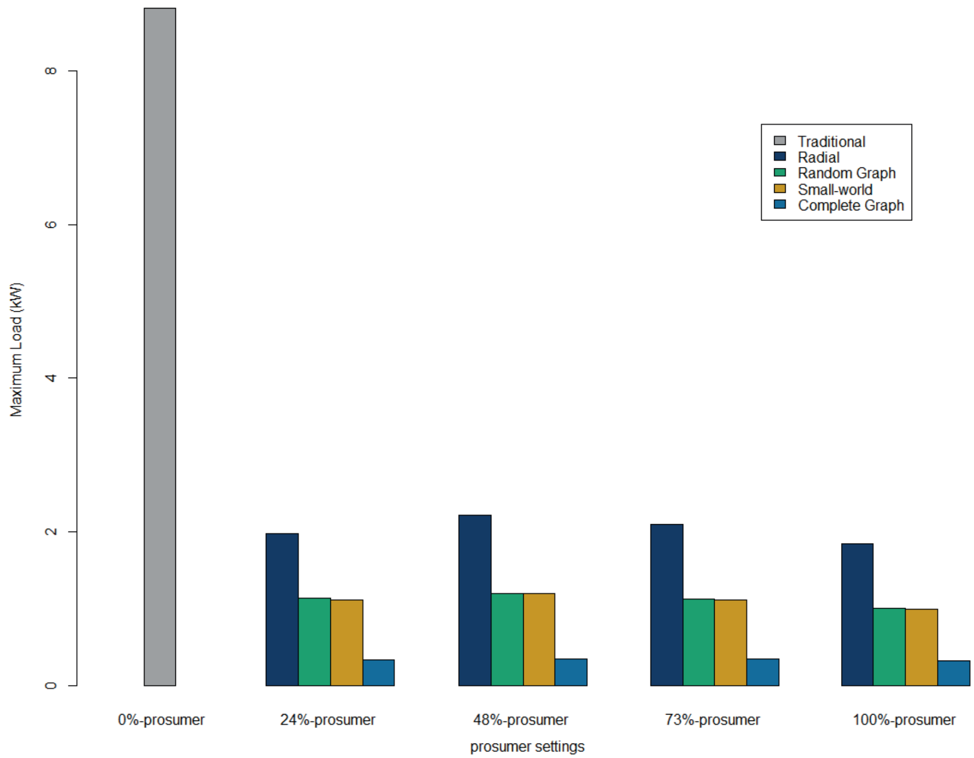


Figure 5.5: Maximum load of the distribution network.

Small-world for the average delivery path length. It achieves the maximum reduction 56.1%.

In summary, the performance of Complete Graph outperforms the other topologies'. Because it has full-meshed topology providing edges for all pairs of nodes. But the Complete Graph is only an idealized model because of its high construction cost in the practical situation. Considering more practical topologies, both of the Small-world and Random Graph perform well in some assessment metrics. The Small-world stands out in two metrics: the maximum load and the energy costs. The Random Graph stands out in other metrics: average delivery path length and energy loss ratio. The performance of average delivery path length and the maximum load is independent of the number of prosumers. However, the performance of energy loss ratio and energy costs is highly relevant to the number of prosumers.

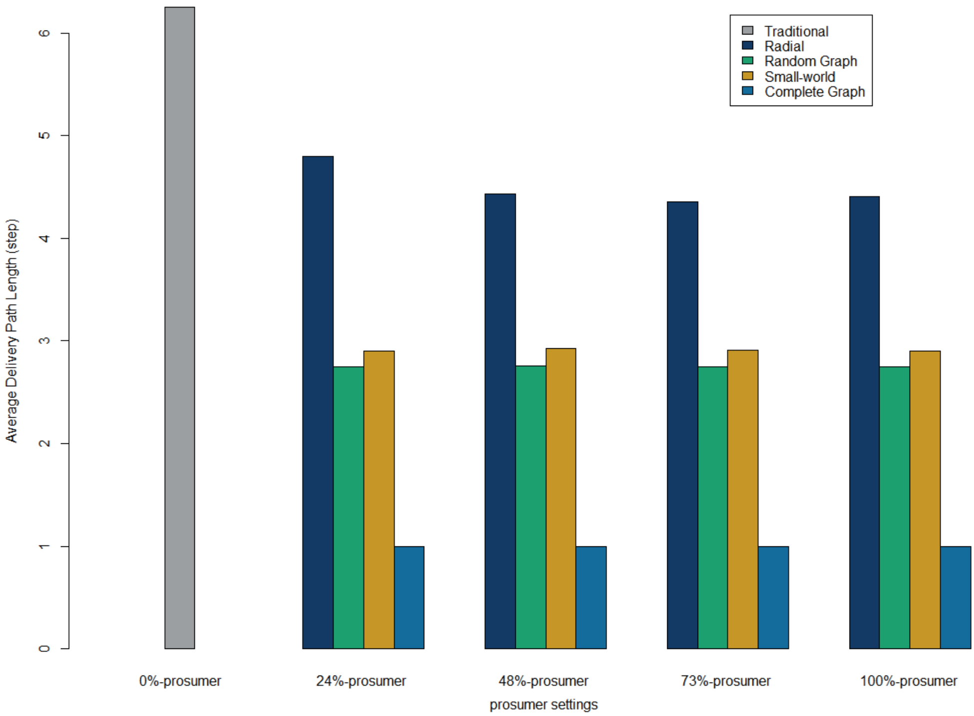


Figure 5.6: Average delivery path length.

Table 5.1: The cases' comparison of the performance.

Metrics / Cases	**Baseline**	**Radial**	**Random Graph**	**Small-world**	**Complete Graph**
Energy Loss Ratio	0.139	−12.9%	−17.3%	−16.5%	−23%
Energy Cost	0.251 €	−6.4%	−7.2%	−7.6%	−8%
Maximum Load	8.808 kW	−79.3%	−88.6%	−88.7%	−96.3%
Average Deliver Path Length	6.25 step	−30.3%	−56.1%	−53.6%	−84%

Parameter Influence on Random Graph and Small-world

In the second stage, our aim is to assess the parameter influence on the small-world and random graph models. For the random graph model, all metrics have a similar trend that is shown in Figure 5.7. As one can see, the value of the assessment metric decreases with the increase of the average degree. Furthermore, the influence of average degree on the random graph model is non-linear. Thus, the speed of the improvement gets slower while the average degree k increases. This means that the performance of the random graph model improves with the increase of its average degree. But the speed of this improvement is attenuates with the increase of the average degree.

For the small-world model, all metrics have a similar shape and trend, as shown in Figure 5.8. The performance decreases with the increasing of the "k" and "p" values. This means that the small-world model's performance improves with the increase of its rewiring probability and average degree. Furthermore, the curves on p-axis (x-axis) and k-axis (y-axis) indicate that the influence of the average degree is much more significant than the influence of rewiring probability. The most significant improvement of the performance happens when "k" increases from 4 to 6. After that, the performance improves less with the increase of "k". Especially when $k > 8$, the speed of performance improvement dramatically reduces. That is, the influence of the average degree on the performance improvement is slight when $k > 8$.

The figures shown above provide an indication of overall trends and shapes of the parameter influence on the small-world model and the random graph model. Overall, the performance of these two models is highly relevant to their parameters. To clearly compare the performance of these two models on the 100-node network, numerical data of the evaluation are also provided. Thus, we select the values at the same average degree "k" (rewiring probability $p = 1.0$ for the small-world model) of these two models for each metric, as shown in Table 5.2 - Table 5.5, for comparison. One notices that the small-world model exceeds the random graph model in most of cases in three metrics, Energy Loss Ratio, Maximum Load and Average Delivery Path Length. The random graph model only has better performance than the small-world model in the metric of Energy Cost. The possible reason is that the small-world model has enhanced propagation speed [137] which makes peer-to-peer energy exchange efficient in the large-scale network. Overall, the small-world model has advantages over the random graph model in the large-scale network.

Table 5.2: Performance comparison of Energy Loss Ratio between the small-world and the random graph.

Average Degree	**Random Graph (RG)**	**Small-world (SW)**	**Model with better performance**
4	0.0741	0.0758	*RG*
6	0.0590	0.0585	*SW*
8	0.0521	0.0517	*SW*
10	0.0480	0.0478	*SW*
12	0.0452	0.0450	*SW*

Table 5.3: Performance comparison of Energy Cost between the small-world and the random graph.

Average Degree	**Random Graph (RG)**	**Small-world (SW)**	**Model with better performance**
4	0.1752	0.1759	*RG*
6	0.1732	0.1735	*RG*
8	0.1722	0.1726	*RG*
10	0.1717	0.1721	*RG*
12	0.1713	0.1717	*RG*

Table 5.4: Performance comparison of Maximum Load between the small-world and the random graph.

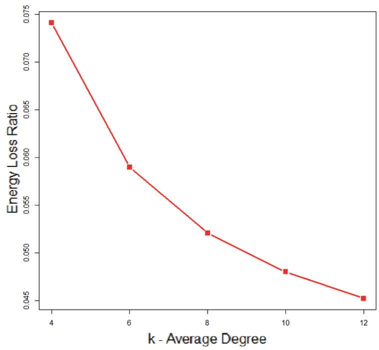
Average Degree	**Random Graph (RG)**	**Small-world (SW)**	**Model with better performance**
4	1.33	1.29	*SW*
6	0.97	0.90	*SW*
8	0.81	0.76	*SW*
10	0.72	0.70	*SW*
12	0.68	0.66	*SW*

Table 5.5: Performance comparison of Average Delivery Path Length between the small-world and the random graph.

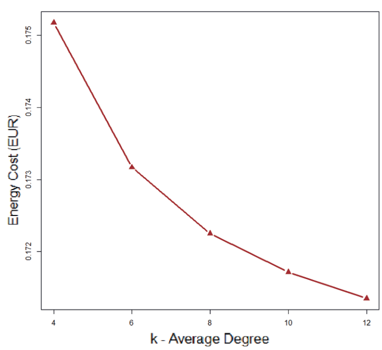
Average Degree	**Random Graph (RG)**	**Small-world (SW)**	**Model with better performance**
4	3.55	3.65	*RG*
6	2.72	2.70	*SW*
8	2.36	2.35	*SW*
10	2.16	2.15	*SW*
12	2.02	2.01	*SW*

5.3 Summary

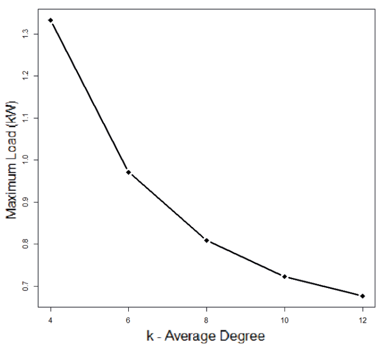
In this chapter, we evaluated the topological effects of the distribution network on peer-to-peer energy distribution. The model and solution of optimizing peer-to-peer energy distribution come from Chapter 4 and is now used to evaluate several topological models under varying generation and load conditions. The evaluation is on the basis of Monte Carlo simulation. We apply various statistical distributions to simulate renewable energy generation, energy consumption of end-users, and real-time prices. For the evaluation, we design four assessment metrics that are: energy loss ratio in the distribution network, energy cost for end-users, maximum load in electric lines, and average delivery path length of energy delivery.



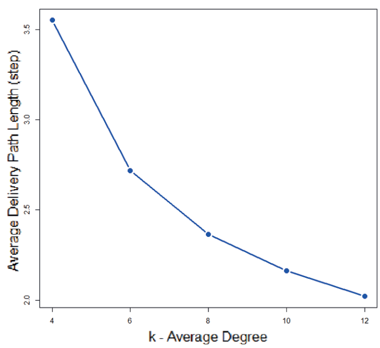
(a) Energy loss ratio of delivery.



(b) Energy costs for end-users.



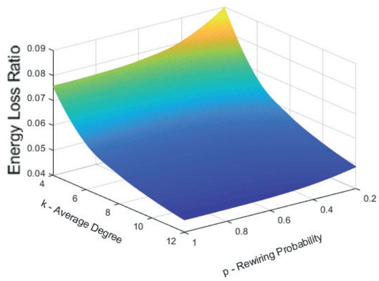
(c) Maximum load of the distribution network.



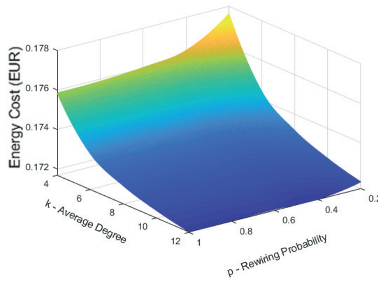
(d) Average delivery path length.

Figure 5.7: Parameter influence on the performance of the random graph model.

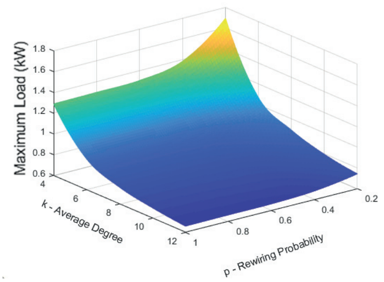
We start with a 37-node radial network. Then we move onto more topological refined models. The random graph model can reduce the average delivery path length when transferring energy from providers to consumers, and energy losses of delivery with respect to other models. On the other hand, the small-world model has higher efficiency than other models in reducing the maximum power load in the distribution network and the cost of obtaining energy by the end-users. The second stage tested on 100-node networks shows that the small-world model outperforms the random graph model in the large-scale network. In addition, the most significant performance enhancement of the small-world model happens when the average degree $k \leq 8$. Thus, the small-world model with $k \in [4, 8]$ is a better choice when we consider the balance between performance and saving on infrastructural costs. This result is in line with the outcomes of the previous work of Pagani and Aiello [106].



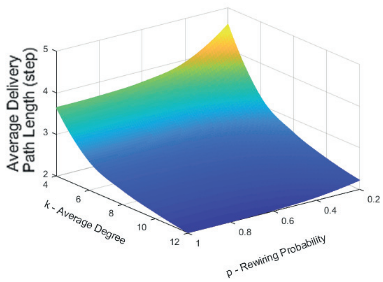
(a) Energy loss ratio of delivery.



(b) Energy costs for end-users.



(c) Maximum load of the distribution network.



(d) Average delivery path length.

Figure 5.8: Parameter influence on the performance of the small-world model.

From a practical point of view, the small-world model appears to have advantages over other models since it can provide a good balance between energy distribution efficiency and the cost of network construction. For the distribution network with dozens of end-users, the small-world model can provide better performance than the random graph model as it requires lower infrastructural/construction costs. For the larger network, since the construction cost of distribution infrastructure rises with the increase of the network scale, the small-world model has a larger advantage over other topology models from an economic perspective. In addition, the small-world model performs better with the higher ratio of prosumers to end-users in the distribution network. Considering the increasing social and economic appeal of becoming a prosumer, the small-world model appears to be a valid design model for energy distribution networks. Such a result confirms the results of the previous work of Pagani and Aiello using different metrics and simulations [106].

Chapter 6

A Strategy for Prosumers' Energy Storage Utilization

We want to go one step further and consider a possible scenario in which the prosumer can provision with energy storage systems to save electrical energy that is produced but not utilized immediately. After fulfilling the individual demands, prosumers can sell and distribute their surplus energy among each other in the same distribution network, or store the energy into their batteries for later self-usage or reselling. In other words, the prosumers can engage in a local energy market bounded by the network it is connected to. This scenario has an important advantage: increasing the independence from centralized schemes for energy generation and operation which is the current adopted model worldwide [48].

Such a scenario also increases the complexity of managing the infrastructure as billing is no longer a centralized service, but rather one that requires distributed transaction management. This requires advanced ICT-based solutions including smart metering infrastructures and market support systems. This chapter focuses on the management of the storage system by each prosumer. We propose a model of battery storage systems to optimize energy costs for prosumers cooperating with the peer-to-peer energy distribution presented in Chapter 4. The model provides foundations for a Home Energy Management System (HEMS) [81] on the basis of Smart Homes [61]. The optimization goal of this model is to reduce energy costs for prosumers. In addition, the proposed model includes an approach for estimating the costs of energy production and storage. We evaluate the model by two assessment metrics: energy cost of prosumers and maximum load in the distribution network. We also studied how the cost of storing energy influences battery storage systems' performance.

6.1 Battery Storage System for Prosumer

In the Smart Grid, end-users include electricity consumers and prosumers. A prosumer produces energy and can store it locally. Meaning that, the prosumer does not have to sell the surplus energy immediately. The prosumer produces energy for its own consumption, or for resell in an open, peer-to-peer energy distribution market. The proposed system includes two parts. The first one models the battery storage system. The second part introduces an approach to estimating the cost of producing and storing energy to assist battery storage systems with decision making, that is, whether to sell, store, or use electricity. Next we provide details of the system we propose.

We continue to use the notations introduced in Section 4.2 of Chapter 4. Thus, we recall that $Q_{t,i}$ represents the amount of energy which the prosumer overproduces or needs at a given time slot. If $Q_{t,i} > 0$, the prosumer has surplus energy to sell or to store. If $Q_{t,i} < 0$, the prosumer needs to buy energy or to discharge the battery storage to fulfill its demand. If $Q_{t,i} = 0$, the produced energy can fulfill the consumption of the prosumer. For a prosumer, the cost of buying an amount of energy x is defined as $CoB(x)$. The energy loss of delivering x to the prosumer is defined as $LoD(x)$ that is the sum of energy losses in electric lines from the provider(s) to the consumer.

A prosumer equipped with a battery storage system can store the surplus energy. When the prosumer needs energy to fulfill its demand ($Q_{t,i} < 0$), it decides to use the stored energy in the battery or to buy energy from available providers. Since our research mainly focuses on the usage of the renewable energy produced by prosumers, we do not consider the case that the battery storage system stores the energy bought from providers, which are possible to be utilities, when energy prices are low, and discharge the energy for selling it at a high price later. The objective of the battery storage system is to reduce energy cost for the prosumer. More precisely, the model of the battery storage system is based on the following assumptions:

- Discharging the battery has priority over buying energy when these two actions have equal cost.
- When overproducing, using the surplus energy to charge the battery has priority over selling it, if these two actions entail equal energy losses.
- The charging and discharging efficiency of the battery is equal.
- The battery can be fully charged and discharged.
- The degradation in charging/discharging performance and energy capacity of the battery is null.
- The storage loss (i.e., self-discharge) of the battery is negligible.
- The charging/discharging process of the battery can be completed at any given time slot.

Formally, for prosumer i, the model is represented in the following way.

- Let $\eta_c \in (0, 1]$ denote the charging efficiency of the battery.
- Let $\eta_d \in (0, 1]$ denote the discharging efficiency of the battery.
- Let $\eta_r = \eta_c \times \eta_d$ denote the round-trip efficiency of the battery.

- Let $SoC_{i,max}$ denote the upper limit of the state of charge, energy capacity (kW·h).
- Let $SoC_{i,min}$ denote the lower limit of the state of charge (kW·h).
- Let $S_{i,max} = SoC_{i,max} - SoC_{i,min}$ denote the maximum amount of energy which the battery can store.
- Let $S_{t,i}$ denote the amount of energy that the battery can discharge at a given time slot.
- Let $\alpha_{t,dis}$ denote the amount of energy provided by the battery at a given time slot.
- Let $\alpha_{t,buy}$ denote the amount of energy bought from other prosumers or the electric utility at a given time slot.
- Let $P_{S_{(t,i)}}$ denote the price of the energy in the battery at a given time slot.
- Let $CoDis(x)$ denote the cost of energy that can be discharged from the battery with amount of x.
- Let $C(x)$ denote the total energy cost of the end-user with amount of x.
- Let CoS denote Cost of Storage that is the cost of using the battery.
- Let CoG denote Cost of Generation that is the cost of renewable energy production by photovoltaic panels and small wind turbines.

Based on the notation above, we are now ready to express the physical and economic constraints of the model. The energy loss of storing $Q_{t,i}$ is $(1 - \eta_r) \times Q_{t,i}$. The model is based on the principle that the battery storage system is useful for balancing energy production and consumption individually, and saving energy costs for prosumers. This goal can be described by the following expression, Equation (6.1).

$$\begin{cases} \min \quad C(|Q_{t,i}|) = CoB(\alpha_{t,buy}) + CoDis(\alpha_{t,dis}) & (Q_{t,i} < 0) \\ \min((1 - \eta_r) \times Q_{t,i}, LoD(Q_{t,i})) & (Q_{t,i} > 0) \end{cases} \tag{6.1}$$

where $LoD(Q_{t,i})$ represents the energy loss of delivering the amount of the surplus energy $Q_{t,i}$.

At each time slot, the sum of discharged and bought energy has to satisfy the total energy consumption of the prosumer. Equation (6.2) represents the system balance constraint.

$$\alpha_{t,dis} + \alpha_{t,buy} = |Q_{t,i}| \tag{6.2}$$

For a prosumer, the strategy of using the battery storage system is to choose the cheaper option between discharging the energy stored in the battery and buying energy from other prosumers or the electric utility when the produced energy cannot satisfy its consumption (underproduction) and the battery is not empty. When the produced energy is over the prosumer's consumption (overproduction) and the battery has space for charging, the strategy is to fully charge the battery and sell the remaining energy to other prosumers or the electric utility. In this strategy, at a given time slot, the amount of energy that can be stored is $S_{i,max} - S_{t,i}$. The energy that can be discharged from the battery is $\eta_d \times S_{t,i}$. The amount of discharged energy is $\frac{|Q_{t,i}|}{\eta_d}$, when the demand can be fully satisfied by discharging the battery. The cost of discharged energy is $\frac{|Q_{t,i}|}{\eta_d} \times P_{S_{(t,i)}}$. The total energy cost for a prosumer is $CoDis(S_{t,i}) + CoB(|Q_{t,i}| - \eta_d S_{t,i})$, when the demand can be partially satisfied by discharging the battery. Thus, at any given time slot, the completed strategy of using the battery storage system of the prosumer i can be described as a decision tree, shown in Figure 6.1.

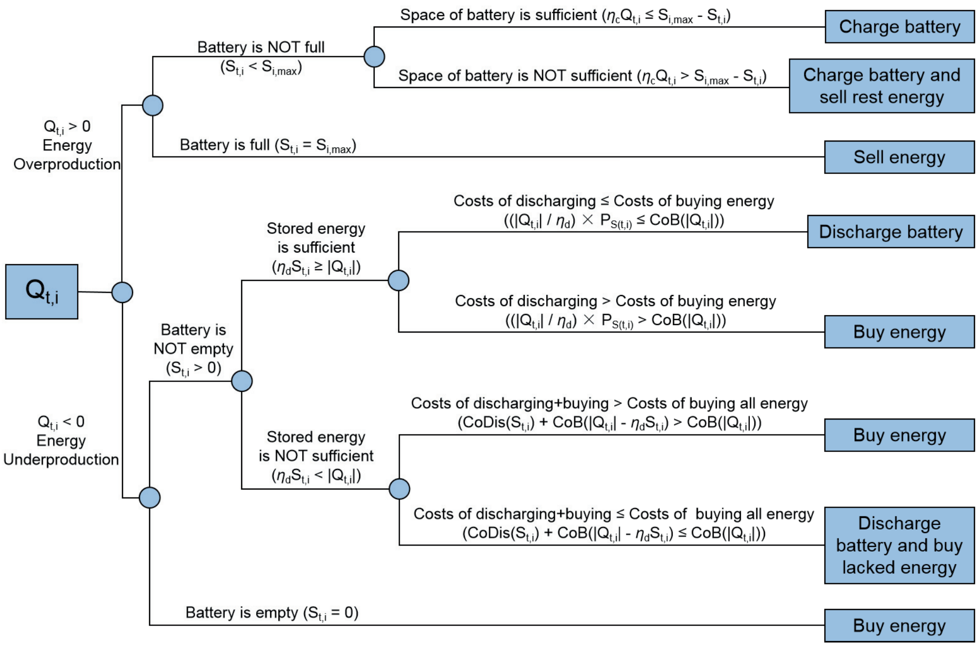


Figure 6.1: Strategy of using the battery storage system.

This decision tree is a key contribution of the proposed model. When renewable energy is overproduced ($Q_{t,i} > 0$), the system checks whether the battery has capacity for storing energy. If the battery has sufficient capacity ($S_{t,i} < S_{i,max}$ and $\eta_c Q_{t,i} \leq S_{i,max} - S_{t,i}$), the overproduced energy is transferred to the battery. If the space is insufficient ($S_{t,i} < S_{i,max}$ and $\eta_c Q_{t,i} > S_{i,max} - S_{t,i}$), the system fully charges the battery and sells the remaining overproduced energy to other end-users by peer-to-peer energy distribution. Otherwise (i.e., the battery is full), all of the overproduced energy is sold. The case of renewable energy underproduction ($Q_{t,i} < 0$) is slightly more complex. If the battery has sufficient stored energy ($S_{t,i} > 0$ and $\eta_d S_{t,i} \geq |Q_{t,i}|$) and the costs of discharging the energy are lower than or equal to the costs of buying the same amount of energy from other prosumers $((|Q_{t,i}|/\eta_d) \times P_{S_{(t,i)}} \leq CoB(|Q_{t,i}|))$, the system discharges the battery to fulfill the demand. If the energy stored in the battery cannot satisfy the demand ($S_{t,i} > 0$ and $\eta_d S_{t,i} < |Q_{t,i}|$) and the costs of discharging the stored energy and buying the missing energy are lower than or equal to the costs of buying the same amount of energy $(CoDis(S_{t,i}) + CoB(|Q_{t,i}| - \eta_d S_{t,i}) \leq CoB(|Q_{t,i}|))$, the system discharges all stored energy from the battery and buys the missing energy from other prosumers. Finally, for the other three branches, the battery is totally empty or discharging the battery is not economically advantageous. The system simply buys all needed energy from other prosumers.

To apply the strategy shown above, $CoDis(x)$ is a key parameter. Here, we define $CoDis(x) = x \times P_{S_{(t,i)}}$. The energy stored in the battery is composed of renewable energy locally produced at some time slots and purchased energy from peer-to-peer energy distribution at some time slots. $P_{S_{(t,i)}}$ is the average price of the local renewable energy and the purchased energy. At any given time slot, $P_{S_{(t,i)}}$ can be calculated as Equation (6.3).

$$P_{S_{(t,i)}} = \frac{\sum\limits_{\forall t \in |T_b|} pc_t \times \alpha_{t,buy} + \sum\limits_{\forall t \in |T_c|} (CoS + CoG) \times \alpha_{t,produce}}{\eta_d \times S_{t,i}} \tag{6.3}$$

where T_b and T_c represent two sets of time slots in which the battery is charged with purchased energy and produced renewable energy, respectively. In a time slot t, the price of purchased energy is pc_t. The amount of purchased energy is $\alpha_{t,buy}$ and the amount of produced energy is $\alpha_{t,produce}$.

To assist the decision making process illustrated in Figure 6.1, we model Cost of Storage (CoS) that is the cost of using the battery storage system, and Cost of Generation (CoG) that is the cost of generating renewable energy. In general, we model CoS and CoG according to the lifetime, costs and outputs of the devices (i.e., renewable energy generators and battery storage systems), formally expressed by Equation (6.4).

$$\frac{\text{Cost of Device}}{\text{(Annual Yield) x Lifetime of Device}} \tag{6.4}$$

6.2 Experimentation

For the evaluation of the proposed model, we resort to stochastic simulations. In particular, we apply the Monte Carlo Simulation approach [77, 110]. Here, we employ the simulation models presented in Chapter 5 to generate renewable energy generation, energy consumption and real-time pricing. Based on the simulation program introduced in Chapter 5, we employ the class of "Energy Storage System" (shown in Figure 3.2) to represent the battery storage system. The Energy Storage System implements the strategy of using the battery storage system (shown in Figure 6.1) and connects the strategy with the peer-to-peer energy distribution proposed in Chapter 4. The class of "Peer-to-peer Energy Distribution" (shown in Figure 3.2), which implements the algorithms presented in Section 4.3, is responsible for calculating $CoB(x)$, the key parameter of the strategy. The program ran on a standard notebook with an Intel® i5-7200U CPU at 2.4 GHz and 16 GB memory. The running of the simulation program took approximately one hour.

6.2.1 Estimation of Device Usage Cost

To evaluate the decision making process of Figure 6.1, we apply Equation (6.4) to estimating Cost of Storage (CoS) and Cost of Generation (CoG). We consider two types of renewable energy generators which are small wind turbines and photovoltaic panels. Therefore, the Cost of Generation includes the cost of generating energy using both wind turbines and photovoltaic panels.

The Cost of Storage is the cost of using the battery storage system. There are various brands of batteries available in the market. We choose the product information of "Tesla Powerwall 1" [10, 9] to estimate Cost of Storage since it is one of the most popular products and representative of current market's state of the art. The total cost of a Tesla Powerwall 1 is approximately €3,161. Its capacity is 6.4 kW·h. For the number of cycles (charge/discharge count), we consider 5,000 cycles as guaranteed under its warranty. Therefore, we calculate the Cost of Storage by the following expression.

$$CoS = \frac{3161\text{ €}}{6.4\text{ kW·h} \times 5000} = 0.1\text{ €/kW·h} \tag{6.5}$$

We separately estimate the costs of generating wind energy and solar energy, and use the average cost of these two generators as the Cost of Generation. We use "Skystream" as the wind turbine for the estimation. A wind turbine of Skystream costs €12,120 [11]. The annual energy yield of this wind turbine is set to 7,192 kW·h per year [11]. It is the average annual wind energy generation at wind speed $5-10$ meters per second. The lifetime of this turbine is 20 years [11]. Thus, the Cost of Generation for wind energy can be calculated by the following equation.

$$\frac{12120\ €}{7192\ \text{kW·h/year} \times 20\ \text{year}} = 0.08\ €/\text{kW·h} \tag{6.6}$$

We consider "Luxor ECO LINE HALF-CELLS M120" as the photovoltaic panel for the estimation because its price can be affordable for residential users and it is in line with similar products. A single photovoltaic panel costs € 149.5 [8]. It has the following characteristics: peak power output 0.31 kWp, efficiency 17.94% (0.1794), surface area 1.66 m^2, warranty 15 years [8]. Moreover, a solar array needs an inverter to convert the direct current generated by photovoltaic panels into alternating current which is fed into the home electricity network. The inverter approximately costs € 208 per kWp [7]. Thus, the total cost of a single photovoltaic panel is $149.5 + 208 \times 0.31 = 213.98$ €. Taking the example of the Netherlands, the average solar power generated by solar radiation in 2018 was 1044.6 kW·h/m^2 [6]. Then, the annual energy yield of a single photovoltaic panel is $1044.6 \times 1.66 \times 0.1794 = 311.1$ kW·h/year. Therefore, the Cost of Generation for solar energy can be calculated by the following equation.

$$\frac{213.98\ €}{311.1\ \text{kW·h/year} \times 15\ \text{year}} = 0.046\ €/\text{kW·h} \tag{6.7}$$

Finally, we apply the average cost of wind and solar energy generation, which is 0.06 €/kW·h, as the Cost of Generation.

6.2.2 Assessment Metrics

We use two metrics to evaluate the effects of battery storage systems on prosumers and the distribution network. Firstly, we measure the energy costs for prosumers in order to evaluate the financial benefits of storage systems. The energy costs are the total amount of money paid by prosumers for storing and buying energy from both prosumers and the electric utility. The energy cost for a prosumer $eu_{t,i}$ at a given time slot is denoted by $COST_{t,i}$. We measure the mean energy cost (unit: EUR) per prosumer per hour (Equation (6.8)).

$$\frac{\sum\limits_{\forall t \in |T|} \sum\limits_{\forall eu_{t,i} \in |EU|} COST_{t,i}}{|EU| \times |T|} \tag{6.8}$$

Secondly, to evaluate the influence on energy distribution flows, we measure the maximum load of the distribution network. The maximum load of an electric line is the maximum energy an electric line carries at a given time slot. We measure the maximum load (unit: kW) of the distribution network which is the maximum value of the loads in all electric lines of the distribution network over a day. The set of all electric lines in the distribution network is E and the load in an electric line e_i at a given time slot is denoted by $LOAD_{t,i}$. Then, we have Equation (6.9).

$$\max_{\forall t \in |T|} \{ \max_{\forall e_i \in |E|} (LOAD_{t,i}) \} \tag{6.9}$$

6.2.3 Case of Distribution Network Topology

To evaluate the efficiency of battery storage systems in distribution networks with different topologies, we run simulations for several topological models. In particular, we consider: a radial model, a random graph model [101], and a small-world model [137]. While the first model represents well the current situation, the other two represent possible, future, meshed networks that can improve the efficiency of local, peer-to-peer energy markets. In particular, the reason for choosing the small-world model is that this model obtains a good balance between energy distribution efficiency and the cost of infrastructure upgrade, as shown for instance in [106]. The radial model is currently the most common network distribution model used in practice and thus can be considered the baseline for the evaluation. On the other hand, the random graph model can be seen as an extreme case of a small-world model where the rewiring probability is set to 100%. Here we apply the 37-node test feeders with radial model (see Figure 5.2(a)), random graph model (see Figure 5.2(b)) and small-world model (see Figure 5.2(c)) introduced in Chapter 5 for simulating the distribution networks.

6.2.4 Case of Battery Storage System Usage

We study the correlation between the Cost of Storage and the frequency of using battery storage systems. We consider the frequency of using battery storage system as the average count of discharging batteries for all prosumers over a day. Our aim is to identify appropriate values of CoS and how the CoS influences battery storage systems' performance. This study is based on the radial distribution network shown in Figure 5.2(a). We increase the CoS from 0 to 0.22 €/kW·h, which is the energy price of the electric utility, to investigate the variation of average count of discharging batteries. More precisely, $CoS = 0, 0.05, 0.1, 0.15, 0.16, 0.17, 0.18, 0.19, 0.2, 0.21, 0.22$ where $CoS = 0$ can be seen as an extreme case of using battery storage systems. The reason of applying the energy price of the electric utility 0.22 €/kW·h is that the prosumer would not be interested in the battery storage system if the CoS is higher than buying energy from the electric utility.

6.2.5 Simulation Setup

To obtain statistical relevance, we set the number of simulation runs per configuration to $2,000$. That is, the program simulates $2,000$ continuous days and calculates the mean values of outputs of these days as the results. These $2,000$ days cover approximately 5.5 years, including all four seasons. Therefore, the seasonal effects are represented in the simulation. In each day, the number of time slots is set to $T = 24$ and $\Delta t = 1$ hour. We consider that all end-users (i.e., nodes) in the distribution network are prosumers and each prosumer is equipped with a battery storage system. At the beginning of the simulation, prosumers randomly choose to either have a wind turbine or photovoltaic panels as their renewable generators.

In our simulation, we use Tesla Powerwall 1 as the battery. Its round-trip efficiency η_r is 92%. Since we assume the battery's charging and discharging efficiency is equal, we have $\eta_c = \eta_d = \sqrt{\eta_r} = 95.92\%$. We set the initial charging states of all batteries to 0. Meaning that all batteries have no energy at the beginning of the simulation. Additionally, the charging state of any battery at the end of any time slot is set to the initial charging state of the same battery at the following time slot. It means that the electrical energy stored in the battery at the time slot t can be still used at the following time slot $t + 1$.

We use €0.22 per kW·h as the price of energy supplied by the electric utility. This is the 2018 average price for the"Euro area" (data from "electricity price statistics"[1]).

6.3 Results

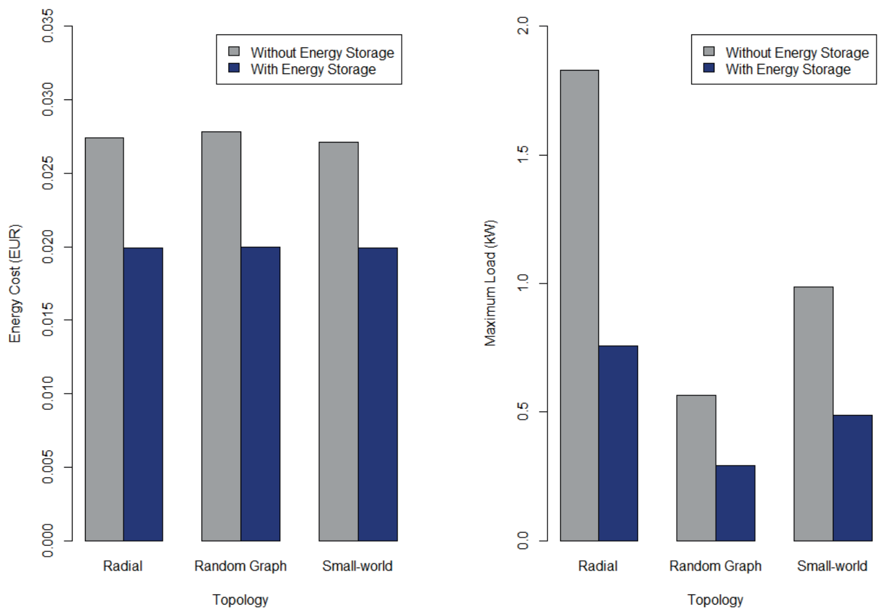
We compare the case in which none of the prosumer has any battery to the case in which each prosumer is equipped with a battery storage system; this we do for each of the three topologies. First, we evaluate the performance of energy cost reduction for prosumers by using battery storage systems. As one can see in Figure 6.2(a), the radial, random graph and small-world models have decreasing energy cost with battery storage systems. The maximum energy cost reduction is 28.3% achieved by the random graph model, compared to the prosumer without battery storage systems on the same topology. The radial model with 27.2% reduction ranks second, and the small-world model with 26.5% reduction is the last one. The maximum performance difference between the three topology models is 1.8%.

Second, we evaluate the maximum load of the distribution network. The simulation results are shown in Figure 6.2(b), where the radial, random graph and small-world models have meaningful reductions compared to the prosumer without battery storage

[1] `http://ec.europa.eu/eurostat/statistics-explained/index.php/Electricity_price_statistics`

systems for the same topology model. The radial model achieves the maximum reduction of 58.5%. The small-world model has 50.7% reduction of the maximum load, ranking second. The last one is the random graph model whose reduction is 48.4%. The maximum performance difference between the three topology models is 10.1%.

Overall, the application of battery storage systems can significantly reduce the energy costs for prosumers and the maximum load of the distribution network at the three evaluated topology models. The reason is that storing the produced renewable energy in battery storage systems for later self-usage has lower costs than buying energy from other prosumers or the electric utility. Moreover, the results show that the topology of the distribution network has a non-negligible influence on the performance of battery storage systems. The topological influence on reducing energy costs is limited. However, the influence on reducing the maximum load of the distribution network is strong.



(a) Energy cost per prosumer per hour. (b) Maximum load of the distribution network.

Figure 6.2: Evaluation results of the metrics.

To study the correlation between the Cost of Storage and the frequency of using battery storage systems, we run the simulation varying the value of Cost of Storage. As shown in Figure 6.3, the count of discharging battery storage systems is around 13.6 times per day with very slight fluctuation. However, the discharging count is always 0 when $CoS > 0.15$. Because the Cost of Storage plus Cost of Generation (0.06 €/kW·h) is equal to or higher than the energy price of the electric utility (0.22 €/kW·h) when $CoS > 0.15$. Then, battery storage systems cannot attract prosumers. Thus, it is not recommended that a prosumer install a battery storage system when $CoS > 0.15$, which is subject to $CoG = 0.06$. Moreover, Cost of Storage does not have significant influence on battery storage systems when $CoS \leq 0.15$.

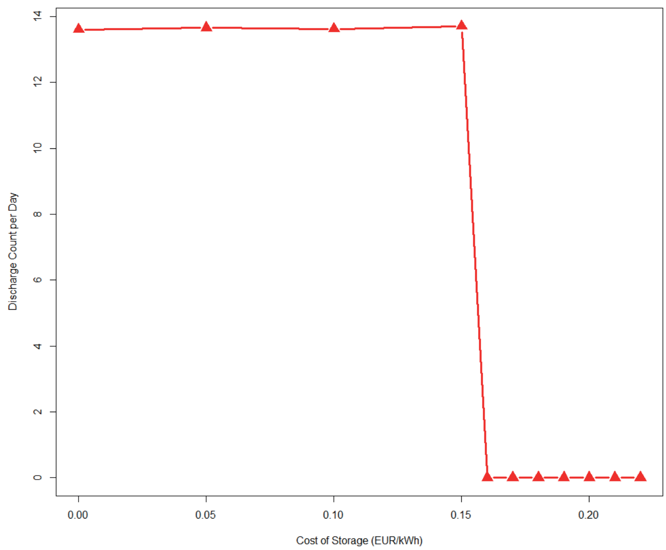


Figure 6.3: The correlation between the Cost of Storage and the frequency of using battery storage systems.

6.4 Summary

In this chapter, we illustrated a model for optimizing the usage of battery storage systems for prosumers based on peer-to-peer energy distribution and free energy trading. This work is intended to provide the foundations for a Home Energy Management System in open Smart Grids. The evaluation is based on Monte Carlo simulations, under varying renewable energy production and load conditions, and distribution network topologies. We apply two assessment metrics that are energy costs for prosumers and maximum load in the distribution network. We run simulations for three topological models: a radial model, a random graph model, and a small-world model. The results show that battery storage systems can significantly reduce the energy costs of prosumers and the maximum load of the distribution network at three evaluated topology models. Moreover, the topology of the distribution network have obvious influence on battery storage systems to reduce the maximum load of the distribution network. However, it has limited influence on reducing energy costs. Compared to the traditional power system, the model of battery storage systems cooperating with peer-to-peer energy distribution has meaningful energy cost reduction for end-users and the investment in the battery is expected to return around 13 years.

Based on realistic energy prices and actual costs of the relevant equipment, we also study the correlation between the Cost of Storage and the frequency of using battery storage systems. According to the results, a prosumer is recommended to install a battery storage system when the Cost of Storage plus Cost of Generation is lower than the energy price of the electric utility. Taking as concrete example Dutch residential houses equipped with photovoltaic panels or small wind turbines, we showed that installing battery storage systems will benefit both end-users and the distribution infrastructure. We expect that for end-users in other European countries, it is possible to get advantages in the energy cost saving by coupling battery storage systems to photovoltaic panels if the national average annual solar radiation is not lower than the one of the Netherlands. Other cases would have to be investigated.

Chapter 7

Conclusion

The vision of a future power grid named Smart Grid [92] where end-users can act as prosumers and supply their own energy demands and exchange surplus energy in an open energy market at local scale, such as the neighborhood, district or city level, is becoming a reality. Compared to the traditional power grid, this vision is more sustainable, efficient and decentralized. Fostered by this inspiration, we have studied a new energy distribution approach and the infrastructural characteristics of the distribution network to support the proposed evolutions for the future energy services and market. To support the Smart Home [61], we have also investigated the strategies for utilizing energy storages equipped by prosumers which provides foundations for a Home Energy Management System (HEMS) [81] in open Smart Grids.

7.1 The Upcoming Revolution in Power Grids

The implementation and standardization of the Smart Grid are under way. In essence, the Smart Grid improves the power system by the functionalities of Information and Communication Technologies to make it more flexible, resilient and efficient. The main aims of the Smart Grid are to realize a high share of renewable energy generation and to provide end-users with more reliable and economic energy services than the traditional power grid.

Our research focuses on three topics: (i) the strategy for peer-to-peer energy distribution to accommodate the energy trading among prosumers in the Smart Grid vision, (ii) the evaluation of topological effects of the distribution network on energy distribution and open trading in a peer-to-peer manner, and (iii) the modeling for optimizing the usage of battery storage systems (BSSs) for prosumers based on peer-to-peer energy distribution and open energy trading.

Our research topics have focused on the distribution network, that is, the low voltage layer of the power grid infrastructure which is closer to the end-user. Considering the first topic of our research, we proposed a novel strategy for optimizing peer-to-peer energy distribution based on the Smart Grid. The novelties of this strategy lie in considering renewable energy production of prosumers, energy loss of delivery, topology of the distribution network, and physical constraints including ampacity of electric lines and directions of energy flows. A mathematical model of the optimization problem, a peer-to-peer model of the Smart Grid, and the optimization algorithms are central to this topic. The models are richer than purely topological ones in considering also basic power flows, while simpler than detailed power flow models traditionally used for modeling power systems in the small. In other terms, one has to find a balance between adequate physical modeling and the scale at which a phenomenon can be observed. Given our interest in looking at possible alternative distribution methods, we chose an intermediate approach between a traditional precise power engineering modeling and a topological/statistical one. Compared with traditional power system design, our strategy can significantly reduce energy loss of delivery, energy costs of end-users, and improve end-users' independence from the electric utility. The study does provide further evidence of the potential of having an open energy market for prosumers, as this is more efficient (see Figure 4.3, Figure 4.7, and Table 4.2), and it makes become a prosumer economically more attractive than the current model where the utilities buy back the over produced energy.

Considering the second topic, we have used the Monte Carlo approach to evaluate topological effects of the distribution network for peer-to-peer energy distribution. Based on the model and solution of energy distribution coming from the first research topic, we evaluated several topological models under varying generation and load conditions. We applied several statistical distributions to generate real-time prices, energy consumption and energy production to assess the maximum load, energy costs, energy loss ratio and average delivery path length for the peer-to-peer energy distribution. The evaluation started with the presently most common radial network and then moved on to more refined topological models: complete graph, the random graph model, and the small-world model. The evaluation results show that the small-world model with the average degree $k \in [4, 8]$ is a better choice when we consider the balance between performance and saving on infrastructural costs. From a practical point of view, the small-world model appears to have advantages over other models since it is able to provide a good balance between energy distribution efficiency and network construction costs. For the distribution network with dozens of end-users, the small-world model can provide better performance than the random graph model as it requires lower infrastructural/construction costs. For the larger network, since the construction cost of distribution infrastructure rises with the increase of the network scale, the small-world model has a larger advantage over other topology models from an economic perspective. In addition, the small-world model performs better with the higher ratio of prosumers to end-users in the distribution network. Considering the increasing social and economic appeal of becoming a prosumer, the small-world model appears to be a valid design model for energy distribution networks. The result of the second topic is in line with the outcomes of the work [106] which uses different metrics and simulations.

Considering the last topic, we have focused on optimizing the usage of battery storage systems for prosumers based on peer-to-peer energy distribution and open energy trading. This work is intended to provide the foundations for a Home Energy Management System in open Smart Grids. The novelties of this topic lie in (i) applying the decision tree to optimizing the battery storage systems and renewable energy usage for prosumers, (ii) modeling the estimation of energy production costs and storage costs, (iii) a proposal for combining battery storage systems with peer-to-peer energy distribution, and (iv) evaluation from the economic point of view on the cost of using battery storage systems. The results show that battery storage systems can significantly reduce the energy costs of prosumers and the maximum load of the distribution networks. Moreover, the topology of the distribution network has obvious influence on battery storage systems to reduce the maximum load of the distribution network. However, the topology of the distribution network has limited influence on reducing energy costs. Based on realistic energy prices and actual costs of the relevant equipment, we also study the correlation between the cost of storage and the frequency of using battery storage systems. According to the results, a prosumer is recommended to install a battery storage system when the cost of storage plus cost of generation is lower than the energy price of the electric utility. Taking as concrete example Dutch residential houses equipped with photovoltaic panels or small wind turbines, we showed that installing battery storage systems benefits both end-users and the distribution infrastructure. We expect that for end-users in other European countries, it is possible to get advantages in the energy cost saving by coupling battery storage systems to photovoltaic panels if the national average annual solar radiation is not lower than the one of the Netherlands.

7.2 Future Directions

The Smart Grid is an evolving research area with more and more pilot projects appearing all over the world. The topics investigated in this thesis are open to further research on the distribution side, energy market side, and end-user side. For the distribution system, several aspects can be considered. Firstly, since the communication technology is such a fundamental element of the Smart Grid [38], two research lines associated with the information communication in the distribution network are foreseeable. The research lines are designing new communication schemes tailored to the peer-to-peer energy distribution and examining their efficiency from a distributed and real-time control point of view. Secondly, the design of the power router based on the peer-to-peer energy distribution should consider the topology of the distribution network. Finally, power flow analysis should be interpreted to move the power routing planning from a theoretical high level to a more fine grained level. The power flow analysis will be based on digital reading that can provide precise data on the power flows in the distribution network.

For the open energy market and trading, transaction costs for buying and selling prosumers' energy should be studied in the future work. The research topics of this thesis only consider distribution costs which are additive to the transaction costs. The transaction costs could be significantly reduced if the number of transactions is very high and thus result in micropayment per transaction. This is for instance the case in the domain of Cloud Computing and Service-Oriented Architectures [112, 75].

From the end-user side, more accurate approaches on the basis of machine learning techniques should be developed to forecast energy production, consumption and real-time energy prices. Along the same lines, the influence on the energy costs paid by the end-user versus the economic advantage of the peer-to-peer energy distribution and open energy trading should be studied. Relevant economic models should be proposed and a detailed analysis on this aspect should be performed to understand the effects on energy bills of end-users.

Additional technical challenges are necessary to be addressed to realize the Smart Grid. To refine the battery storage system for the residential building (i.e., home battery), the battery model should be improved, in particular by relaxing the assumption on no self-discharge and capacity degradation of batteries. Moreover, the economic benefit of selling energy in the battery storage system to other end-users can be investigated. This entails the addition to the model of optimization strategies for charge/discharge cycles and the enabling of prosumers to decide whether the energy stored in the battery should be sold to other end-users for an immediate profit.

The introduction of the electric vehicle (EV) will also play an important role in the future of the (smart) grid. The electric vehicle has obvious advantages in terms of its low or even null carbon emission compared to conventional vehicles [32]. However, with the rising number of the electric vehicles, the EV charging load increases the total required load capacity of the distribution network and also is the cause of randomness and uncertainty on the load [138]. To address such issues, the current research mainly focuses on the load modeling-based impact analysis and control strategy [138]. We propose applying the battery storage system to decreasing the EV charging load in the distribution network under the control of the Home Energy Management System. This entails the addition to the model of optimization strategies for the battery storage system considering charge/discharge cycle of the EV's battery. Considering the electric vehicle is not always connected to the Home Energy Management System, the battery storage system can charge the EV's battery by its buffering effect as shown in Figure 7.1. It means that the battery storage system can save the surplus renewable energy or buy energy with cheap prices during the off-peak hours and charge the EV's battery during the rush hours to reduce the load in the distribution network. For example, the battery storage system saves the energy produced by the photovoltaic panels during the daytime while the householder drives the electric vehicle away. When the electric vehicle returns to the house and connects to the Home Energy Management System, the battery storage system (partially) charges the EV's battery using the energy saved in the daytime. In addition, the electric vehicle can also be considered as a part of the battery storage system to support the energy usage of the residential building when it has surplus energy after fulfilling its energy demand of driving. This proposal provides a fully usable model for the Home Energy Management System to realize the Smart Home on the basis of the Smart Grid.

Considering the application side, new software systems should be designed for the Smart Grid. On the side of the peer-to-peer energy distribution, the software should be enhanced with agent technology for market interaction which enables end-users to share the trading information such as the data of energy providers, consumers and prices. On the side of the battery storage system, artificial intelligence technologies can support the prediction of energy production, consumption and real-time energy prices, and perform the decision making according to the predicted information, user preferences and be aware of external conditions.

The Smart Grid is nowadays more a vision than a reality [38]. In the path of evolving the current power grid, there are several unavoidable barriers that should be considered. First, implementing the Smart Grid will require higher investment than implementing the traditional power grid. Specifically for the peer-to-peer energy distribution, small-world networks normally have more electric lines than radial networks. Moreover, deploying power routers and highly efficient communication networks are also essential for the peer-to-peer energy distribution. Such infrastructures cause more construction costs than implementing the traditional distribution systems. Second, the resistance from power engineers of the power system industry exists. Some power engineers are against the ideas of evolving topologies of distribution networks. They believe that the meshed distribution networks are not physically feasible in real-world cases and the present radial distribution networks do not have any necessity to evolve because they have well worked for many years. Finally, the traditional electric utilities would not welcome the Smart Grid. Because the open energy market and trading significantly reduce the end-users' dependency on these companies and threaten monopoly enterprises in the electricity markets.

The future directions and development barriers associated with the research topics described in Section 7.1 depend on the transition towards the Smart Grid. In the transition, different regions may follow different paths at different speeds.

Many conditions can influence the transition, such as the available natural resources, economy environment, energy policies, and attitudes of the government and monopoly enterprises in the electricity markets. Overall, realizing the Smart Grid pushes the transition towards a sustainable future where distributed renewable energy sources are highly integrated into the power grid and provide higher flexibility and reliability for green energy usage.

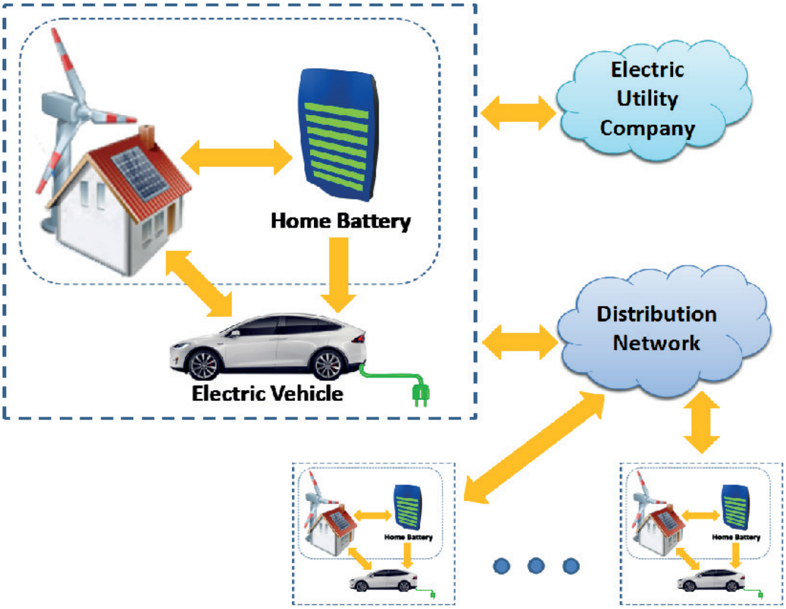


Figure 7.1: A fully usable model for the Home Energy Management System (HEMS) considering the electric vehicle.

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